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Automated Monitoring Systems to Assess Gait Score and Feed Intake of Broilers

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Dissertation presented in partial fulfilment of the requirements for the degree of PhD in Bioscience Engineering

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Summary

The last decades of the 20^{th} century saw important changes in animal production. Production intensified considerably and farms became highly specialised. Traditionally, livestock management decisions were based on the observation and judgment of the farmer. However, because of the increasing scale of farms and the large number of animals, the farmer has a high technical, organisational and logistical workload and therefore has limited time to monitor his animals himself.

Automated monitoring and control systems are complementary to human observation, and are becoming increasingly useful as a means of supporting farm management. Both the growing demand for objective data and the availability of cheap technology result in better monitoring practices for animal applications. Demand for monitoring systems will increase due, in particular, to the high demand for meat worldwide and the occurrence of disease epidemics on a global scale, both among animals and as a result of disease transfer from animals to humans. Technology which can indicate the health or welfare status of individual animals can contribute to more efficient management or treatment. This thesis discusses a number of applications of Precision Livestock Farming technology for monitoring welfare aspects of broiler chickens.

The general objective of this thesis is to explore whether technology can assist the eyes and ears of a farmer for large groups of animals. The first objective is to assess the potential for extracting physiological and behavioural information from a group of broilers during growth by taking only image information into account. More specifically, automatic image monitoring systems which measure the activity, exploration, locomotion and posture behaviours of broiler chickens in relation to their lameness degree (gait scores) were implemented. This was done by using a fixed camera to automatically and continuously monitor changes in the physiological and behavioural status of broiler chickens by also taking into account the individuality of the animals.

Chapter 2 describes a fully automatic monitoring technique to measure the activity levels of broiler chickens in relation to their lameness degree (gait scores). The advantage of this method is that it captures images with a fixed background. Segmentation is much more precise and animals can easily and accurately be extracted from continuous image recordings. Overall, the results show that automatic camera monitoring systems can provide an automatic tool for measuring activity in relation to gait score. Monitoring activity alone is not an ideal

way of assessing lameness in broilers. Therefore Chapter 3 extends existing research on the activity of broiler chickens and describes a novel system for automatic assessment of use of space by chickens with different gait scores using imaging technology. A novel monitoring system with colour tracking features was developed and used to detect use of space by broiler chickens and to link it with lameness, instead of focusing exclusively on the activity of broiler chickens in order to identify the relationship with the gait score (lameness) of birds. Use of space by chickens with a certain gait score seems to be strongly related to their activity level and gait score, suggesting that use of space may also be an indicator for lameness.

In field conditions, it is not easy to measure activity and use of space due to the limited space available and the bird density in broiler houses, especially during the latter stages of the growing period. Chapter 4 therefore describes a novel technique for capturing the shape of a bird based on the a-b dimension (length-width) and centre point of the animal. A first order transfer function (TF) modelling technique can be used to represent the shape of the bird on the basis of a limited number of parameters. This chapter discusses the use of dynamic changes in the calculated variables, such as x-position, y-position, orientation and the back area of chickens, as a measure of biological status in order to assess lameness by investigating the locomotion behaviour and body posture of broilers. Strong correlations were found between the locomotion behaviour and gait score level of broiler chickens. There was also a strong correlation between the gait score level and body posture of birds. The results suggest that this automatic monitoring system has potential to be used as a tool for assessing lameness in broiler chickens. In addition to the previous findings in cows and pigs, this technology also proved to be effective at detecting lameness in broilers. Other studies have shown that it is effective at detecting lameness in large animals, but the theory that this technology could be used for broiler chickens has never been accepted as there are thousands of animals in one confined space and side view monitoring is not possible. One of the most remarkable findings of this PhD thesis is that vision technology (top view monitoring) and Precision Livestock Farming (PLF) approaches can be used to detect lameness in broiler chickens. New technological developments make it more feasible to monitor welfare parameters in groups of thousands of animals.

The earlier chapters of this thesis describe the development of fully automated continuous monitoring systems to assess the health and welfare of broilers based on vision technology. The results from previous chapters show that the weight of seriously lame birds is significantly lower (p < 0.05). In addition to animal health and welfare, the environmental impact of livestock production and feed use efficiency are also very important issues. This led

us to evaluate the next hypothesis, presented in Chapter 5, which states that automatic recording of pecking sounds from broilers allows measurement of feed intake and assessment of the feeding behaviour of chickens in real time. Therefore, having investigated lameness in broiler chickens by means of vision technology using different monitoring techniques, Chapter 5 goes on to examine feeding behaviour on the basis of sound analysis. A novel method for automatic detection of pecking sounds from broiler chickens was developed and the feed intake of birds was automatically quantified. This chapter describes how the overall sound within a certain environment, in this case an experimental area, was continually recorded by means of a microphone attached to the feeder. The advantage of this contact microphone in the feeder is that it captures all sounds around the feeder, especially pecks by birds. The correlation between the number of pecks and the feed intake of chickens was very high at $R^2 = 0.985$. The results show that this pecking sound detection system has the potential to be used as a tool to monitor the feed intake of chickens. The advantage of this system is that measurements can be made continuously throughout the life-span of a flock, in a fully automated, completely non-invasive and non-intrusive way.
Moving from a simple process (detecting pecks by single birds) to a slightly more complex situation (detecting pecks by multiple birds while the birds were eating together), the feeding behaviour of broilers was then assessed by improving the existing algorithm. Chapter 6 extends the existing research into the feed intake of broiler chickens and describes a monitoring system for accurate measurement of the feed intake of broiler chickens at group level using a real-time sound processing technology. The results suggest that it will be possible to test this system in field conditions thanks to the low cost and applicability of this technique. Thus, future research should focus on sound technology as a means of assessing the health and welfare of broilers by accurately and continuously monitoring feeding behaviour.

This thesis demonstrates that health and welfare related behaviour in broiler chickens can be monitored continuously throughout their life using image and sound technology, in a fully automated and non-invasive way.

The overall conclusion of this thesis is that, depending on the complexity of the image and sound signal and the stocking density ($birds/m^2$) of the broiler chickens monitored (either in a group or individually), image or sound information alone or a. combination of image and sound information allows quantification of the biological status, health and welfare of broiler chickens in real time.

Samenvatting

De laatste decennia van de 20ste eeuw werden gekenmerkt door belangrijke veranderingen in de dierproductie. De dierproductie werd veel intensiever en veehouderijen werden in sterke mate gespecialiseerd. Traditioneel werden beslissingen in het veeteeltmanagement gebaseerd op de waarneming en de beslissing van de veehouder. Door schaalvergroting van de veehouderijen en het groot aantal dieren heeft de veehouder echter een hoge technische, organisatorische en logistieke werklast. Hierdoor hebben veehouders steeds minder tijd om hun dieren op te volgen.

Als aanvulling op de menselijke waarneming wordt er steeds meer gebruik gemaakt van geautomatiseerde monitorings- en besturingssystemen ter ondersteuning van het veeteeltmanagement. Zowel de toenemende vraag naar objectieve data als de beschikbaarheid van goedkope technologie resulteren in betere monitoringsystemen voor diertoepassingen. Vooral omwille van de grote wereldwijde vraag naar vlees en het voorkomen van epidemieën op wereldschaal, zowel bij dieren onderling als van dier op mens, zal er een toenemende vraag zijn naar monitoringsystemen. Technologie die de gezondheids- of welzijnstoestand van individuele dieren kan opvolgen, kan bijdragen tot een efficiënter management of een verbeterde behandeling. Dit proefschrift behandelt verschillende toepassingen van precisieveeteelttechnologie voor het monitoren van de welzijnsaspecten van vleeskuikens.

De algemene doelstelling van deze thesis was om te onderzoeken of technologie de ogen en oren van een veehouder kunnen vervangen in grote dierengroepen. De eerste doelstelling was om te beoordelen of het mogelijk is om fysiologische en gedragsinformatie van een groep vleeskuikens tijdens de groei vast te leggen door gebruik te maken van informatie uit camerabeelden. Er werden daarom automatische camera monitoring systemen geïmplementeerd die in staat zijn de activiteit, exploratie, locomotie en houding van vleeskuikens te meten en in verband te brengen met hun graad van kreupelheid (locomotiescore). Dit werd gerealiseerd met behulp van een vaste camera om automatisch en continu de veranderingen van deze fysiologische en gedragstoestanden te monitoren door rekening te houden met de individualiteit van de dieren. In hoofdstuk 2 werd een volledig geautomatiseerde techniek ontwikkeld om activiteitsniveaus van vleeskuikens te meten in relatie tot hun graad van kreupelheid (locomotiescore). Het voordeel van deze methode is dat beelden worden vastgelegd met een vaste achtergrond. De segmentatie is dan veel accurater en de dieren kunnen eenvoudig en nauwkeurig geëxtraheerd worden uit de continue beeldopnamen. Over het algemeen tonen de resultaten aan dat een automatisch

cameramonitoringssysteem een hulpmiddel kan zijn bij het bepalen van activiteit in relatie tot de locomotiescore. Het monitoren van enkel activiteit was echter niet voldoende om de kreupelheid van de vleeskuikens te beoordelen. Daarom werd er in hoofdstuk 3 verder gebouwd op bestaand onderzoek betreffende de activiteit van vleeskuikens. Het hoofdstuk beschrijft een nieuw systeem dat in staat is om automatisch het ruimtegebruik van vleeskuikens met verschillende locomotiescores te beoordelen via beeldverwerkings technologie. In plaats van enkel te focussen op de activiteit van vleeskuikens om de graad van kreupelheid te bepalen, werd een nieuw systeem ontwikkeld dat kleureigenschappen opvolgt om op die manier het ruimtegebruik van de vleeskuikens te detecteren en te linken met kreupelheid. Het ruimtegebruik van vleeskuikens met een bepaalde locomotiescore blijkt sterk gerelateerd te zijn met hun activiteitsniveau en de locomotiescore en daarom kan ruimtegebruik ook een indicator zijn voor kreupelheid.

In de praktijk zijn activiteit en ruimtegebruik moeilijk te bepalen door de beperkte vrije ruimte en bezettingsdichtheid in pluimveehouderijen en dit vooral in de latere fasen van de groeiperiode. Daarom werd er in hoofdstuk 4 een nieuwe methode geïntroduceerd om de vorm van de dieren te bepalen op basis van de a-b (lengte-breedte) en het middelpunt van de dieren. Door gebruik te maken van een eerste orde transferfunctie (TF) modelleertechniek, kan de vorm van het vleeskuiken voorgesteld worden aan de hand van slechts een beperkt aantal parameters. Dit hoofdstuk introduceert het gebruik van dynamische veranderingen van de berekende variabelen zoals de x-positie, de y-positie, de oriëntatie en de oppervlakte van de rug als maat voor de biologische toestand. De kreupelheid werd beoordeeld op basis van de locomotie en houding van de vleeskuikens. Er werden sterke correlaties gevonden tussen de motoriek en de locomotiescore van de vleeskuikens. Daarnaast was er ook een sterke correlatie tussen de locomotiescore en de houding van de vleeskuikens. De resultaten suggereren dat dit automatisch monitoringssysteem het potentieel heeft om gebruikt te worden als tool voor de beoordeling van kreupelheid bij vleeskuikens. Naast de eerdere bevindingen bij koeien en varkens, heeft deze technologie nu ook bewezen efficiënt te zijn voor het opsporen van kreupelheid bij vleeskuikens. Andere studies waren in staat op een efficiënte manier kreupelheid te detecteren bij grote dieren, maar het idee om deze technologie toe te passen bij vleeskuikens leek onmogelijk doordat duizenden dieren samenzitten in een beperkte ruimte en omdat monitoring vanuit zijaanzicht niet mogelijk is. Een van de meest merkwaardige bevindingen van dit doctoraatsproefschrift was dat kreupelheid van vleeskuikens via het gebruik van cameratechnologie (monitoring vanuit bovenaanzicht) en een precisieveeteeltbenadering kan gedetecteerd worden. Dankzij deze nieuwe technologieën wordt het mogelijk om welzijnsparameters te schatten voor groepen van duizenden dieren. In de voorgaande hoofdstukken werd een volledig geautomatiseerd monitoringssysteem ontwikkeld voor de beoordeling van de gezondheid en het welzijn van vleeskuikens via beeldverwerkingstechnologie. De resultaten van de vorige hoofdstukken tonen aan dat heel kreupele dieren een significant lager gewicht hebben ($p > 0.05$). Naast diergezondheid en welzijn zijn ook voederefficiëntie en impact van dierproductie op de omgeving erg belangrijke kwesties. Dit bracht ons tot de evaluatie van de hypothese in hoofdstuk 5, waarin gesteld wordt dat het mogelijk is om met behulp van automatische registratie van pikgeluiden van vleeskuikens voeropname te meten en eetgedrag te beoordelen in real-time.

Daarom werd na het controleren van kreupelheid bij vleeskuikens via beeldverwerkingstechnologie, het eetgedrag onderzocht via geluidsanalyse. Er werd een nieuwe methode ontwikkeld voor de automatische detectie van pikgeluiden en voor de automatische kwantificatie van voeropname van de vleeskuikens. In dit hoofdstuk werden alle geluiden in een bepaalde ruimte (in dit geval een onderzoekskamer) continu opgemeten via een microfoon die aan de voederbakken werd vastgemaakt. Het voordeel van deze methode was dat de microfoon alle geluiden rond de voederbak opmat en dan vooral de pikgeluiden. De correlatie tussen het aantal pikgeluiden en de voeropname was zeer hoog ($R^2 = 0.985$). De resultaten tonen aan dat een systeem voor de detectie van pikgeluiden het potentieel heeft om gebruikt te worden als hulpmiddel voor het monitoren van voeropname bij kippen. Het voordeel van dit systeem is dat metingen continu gedaan kunnen worden gedurende de levensduur van een groep vleeskuikens en dit op een volledig geautomatiseerde, niet-invasieve en niet-hinderende manier.

Om te gaan van een eenvoudig proces (de detectie van enkelvoudige pikgeluiden) naar een meer complex probleem (detectie van verschillende pikgeluiden, wanneer de dieren allemaal tegelijk aan het eten zijn) werd het bestaande algoritme uitgebreid. Hoofdstuk 6 bouwt verder op bestaand onderzoek naar voeropname bij vleeskuikens en beschrijft een monitoringssysteem dat aan de hand van geluidsverwerkingstechnologie nauwkeurig de voeropname op groepsniveau opmeet. De resultaten suggereren dat het mogelijk is om het systeem in de praktijk te testen omwille van de lage kosten en toepasbaarheid van het systeem. Daarom zouden toekomstige onderzoekers moeten focussen op geluidstechnologie om het welzijn en de gezondheid van de vleeskuikens nauwkeurig en continu te monitoren via hun eetgedrag. In dit proefschrift werd aangetoond dat het gedrag van vleeskuikens, dat gerelateerd is aan gezondheid en welzijn, continu kan gemonitord worden door gebruik te maken van beeld- en geluidstechnologie en dit op een volledig automatische en niet-invasieve manier. Daarnaast kan ook toekomstig gedrag van de vleeskuikens voorspeld worden aan de hand van wiskundige modellen en kan dit gedrag ook gecontroleerd worden via toepassingen van de moderne controletheorie.

De algemene conclusie van dit proefschrift is dat de biologische toestand, de gezondheid en het welzijn van de vleeskuikens in real-time gekwantificeerd kunnen worden via enkel geluid- of beeldinformatie of via een combinatie van beide afhankelijk van de complexiteit van het beeld- en geluidssignaal en de bezettingsdichtheid (vogels/m²) van de vleeskuikens die gemonitord worden (in groep of individueel).

Abbreviations and symbols

List of abbreviations

- **AMEn**: Apparent Metabolisable Energy
- **CCTV**: Closed-circuit television
- **CITD**: Complex, individual, time-varying and dynamic
- **FAO**: Food and Agriculture Organisation
- **FAWC**: Farm Animal Welfare Council
- **FCR**: Feed Conversion Ratio
- **FIPE**: Feed intake per experiment
- **FIPP**: Feed intake per peck
- **FP**: False positive
- **FUPE**: Feed uptake per experiment
- **FWPE**: Feed wastage per experiment
- **GDP**: Gross domestic product
- **GS**: Gait Score
- **LTL**: Latency to lie down test
- **NOL**: Number of lying events
- **NPPE**: Number of pecks per experiment
- **PLF**: Precision Livestock Farming
- **RGB**: Red-green-blue
- **SCAHAW**: Scientific Committee on Animal Health and Animal Welfare
- **SQL**: Structured query language
- **TF**: Transfer Function
- **TP**: True positive
- **WQ**: Welfare Quality

List of Symbols

- **I**: Intensity of the pixel
- **x,y**: Coordinates
- **t**: Time
- **Ia**: Activity image
- **ai**: Activity index
- **Zi**: Zone
- x^2: Chi-squared
- **xc,yc**: Centre coordinates of bird
- α**:** Rotation angle around the horizontal axis
- **a,b**: Lengths of the major and minor axis

Contents

Acknowledgments ..... **i**

Summary ..... **iii**

Abbreviations and symbols ..... **x**

Contents ..... **xii**

List of Figures ..... **xvi**

List of Tables ..... **xviii**

1. General Introduction **1**

1.1. Modern Livestock 1

1.1.1. Importance in the world 1

1.2. Problems 3

1.2.1. Productivity 3

1.2.2. Environmental impact 4

1.2.3. Animal health and welfare 6

1.3. General Method: Precision Livestock Farming (PLF) 9

1.3.1. PLF technology 11

1.3.2. Sensors and sensing 12

1.4. Hypothesis and objectives 13

1.5. Main framework of this thesis 14

1.6. Link with other chapters 15

2. Application of a fully-automatic analysis tool to assess the activity of broiler chickens with different gait scores **16**

2.1. Introduction 17

2.2. Materials and Methods..18
2.2.1. Birds, Experimental Design and Video Recordings 18
2.2.2. Image calibration..20
2.2.3. Activity measurements 20
2.2.4. Statistical Analysis 21
2.3. Results...21
2.3.1. Activity and Gait Score 21
2.4. Discussion and Conclusions..25
2.5. Link with other chapters...26
3. Automatic Identification of Activity and Spatial Use of Broiler Chickens with Different Gait Scores 27
3.1. Introduction...28
3.2. Materials and Methods..30
3.2.1. Experimental Setup and Equipment 30
3.2.2. Birds 31
3.2.3. Experiments...31
3.2.4. Camera Calibration...33
3.2.5. Image Analysis 33
3.2.6. Activity Calculation 33
3.2.7. Calculation of use of space by chickens 35
3.2.8. Statistical Analysis 35
3.3. Results...36
3.3.1. First Experiment 36
3.3.2. Second Experiment 39
3.4. Discussions 42
3.5. Conclusions...44
3.6. Link with other chapters...44
4. Automatic classification of measures of lying to assess the lameness of broilers.. 45
4.1. Introduction...46
4.2. Materials and Methods..48
4.2.1. Experimental Design, Video Recordings and Birds 48
4.2.2. Image analysis 50
4.2.3. Classification of lying behavior...51
4.2.4. Statistical Analysis 52
4.3. Results...52

4.3.1. Classification of Lying 52
4.3.2. Assessment of lying behaviour in relation to gait score 54
4.4. Discussions 56
4.5. Conclusions 58
4.6. Link with other chapters 59
5. A novel method to automatically measure the feed intake of broiler chickens by sound technology 60
5.1. Introduction 61
5.2. Materials and Methods 62
5.2.1. Experimental setup 62
5.2.2. Birds and housing 63
5.2.3. Definition of frequency ranges 64
5.2.4. Filtering 64
5.2.5. Sound Extraction 65
5.2.6. Sound Classification 65
5.2.7. Feed Intake Calculation 66
5.3. Results 67
5.4. Discussions 71
5.5. Conclusions 72
5.6. Link with other chapters 73
6. A Real-Time Monitoring Tool to Automatically Measure the Feed Intakes of Multiple Broiler Chickens by Sound Analysis 74
6.1. Introduction 75
6.2. Materials and Methods 76
6.2.1. Experimental Setup 76
6.2.2. Birds and Housing 77
6.2.3. Definition of frequency ranges 77
6.2.4. Filtering 77
6.2.5. Sound Extraction 78
6.2.6. Sound Classification 79
6.2.7. Feed Intake Calculation 80
6.3. Results and discussion 80
6.4. Conclusions 84
7. General Discussion and Conclusions 85
7.1. Problems of Modern Livestock and Disadvantages of Manual Assessment 85

7.2. Automated measuring of health and welfare indicators in modern livestock....88

References....95

Curriculum Vitae....104

Publications....105

Patent....107

List of figures

1.1	World production of main categories of meat from 1961 to 2012 (FAO 2012).	2
1.2	Production of poultry and pig meat in BRIC countries (China, India and Brazil) from 1961 to 2012 (FAO 2012).	3
1.3	Schematic overview of PLF to control biological processes such as animal behaviour, physiology and growth (Aerts et al. 2003)	11
2.1	Laboratory set-up with a computer, camera and cages with five chickens in each compartment.	19
2.2	One example of continuous activity index measurement of GS3 group chickens during 3-h experiment 1 (a) and experiment 2 (b).	22
2.3	Activity index of chickens with different gait scores during experiment 1 (a) and experiment 2 (b).	23
2.4	Correlation between gait scores, activity and weight of the broiler chickens	24
2.5	One example of the cumulative activity index of chickens with different gait scores during experiment 1 (a) and experiment 2 (b), over three hours	24
3.1	(a) test installation, (b) integrated pens, (c) merged chickens	30
3.2	One example of continuous activity index measurement of GS3 group chickens during 3-h experiment.	36
3.3	(a) total activity index of gait scores, (b) daily cumulative activity of all gait score groups over six measurement days, and (c) relationship among gait score, weight, and activity.	37
3.4	(a) total activity index of gait scores, (b) daily cumulative activity of three gait score groups over six measurement days, and (c) relationship among gait score, weight, and activity.	40
3.5	Space use pattern of the three gait score groups investigated.	41
3.6	Number of areas visited by the chickens	41
4.1	The test corridor and the video recording equipment (a), an image of the recorded video (b)	49
4.2	Flowchart of the image analysis and classification procedure	51
4.3	Walking trajectory of chicken 1 during the experiment.	52
4.4	The ellipse and the centre point of broiler chickens.	53
4.5	X position, Y position and the orientation changes (degrees) of chicken 1 during experiment.	53

4.6	The number of lying events for broiler chickens (a) NoL obtained by algorithm, (b) NoL obtained by manual labelling.	55
4.7	Latency to lie down in broiler chickens.	56
4.8	Correlation between gait scores, lying and LTL behaviours of broilers and comparison of algorithm output against manual labelling.	56
5.1	Laboratory setup for sound recordings of an individual chicken.	63
5.2	Filtered sound signal (pecking and other) between 1 kHz and 5 kHz.	64
5.3	The flowchart used for the proposed algorithm.	64
5.4	Continuous recording of sounds (top) and individual pecking sounds (bottom) as extracted by the algorithm.	66
5.5	Spectrogram of a continuous sound (consisting of 13 pecking hits) represented in the time domain (top) and in the frequency domain	66
5.6	The relationship between feed uptake and number of pecks by chickens per experiment.	67
5.7	The correlation between feed uptake per minute and number of pecks per minute.	70
5.8	The relationship between feed intake per experiment and number of pecks per experiment.	70
5.9	An example of the relationship between number of pecks and feed uptake by chickens.	71
6.1	General setup with experimental materials (a), an example of a recorded top view image (b).	76
6.2	Filtered sound signal between 4 kHz and 5 kHz.	78
6.3	The flowchart for the proposed signal processing.	78
6.4	Continuous recording of sounds (top) and individual pecking sounds (bottom) as extracted by the algorithm.	79
6.5	Spectrogram of a continuous sound represented in the time domain (top) and in the frequency domain (bottom).	80
6.6	Correlation between feed intake measured by algorithm and feed intake recorded by a weighing scale.	83
6.7	Correlation between feed intake and relational error of algorithm	83

List of tables

2.1	Daily numbers of frames and recording times during the experiments.	20
2.2	Statistical analysis of different gait scores.	22
2.3	Statistical analysis of the activity index, weight and body area of broiler chickens	23
3.1	Overview of chickens used in the experiments.	32
3.2	Video recording times and number of frames.	32
3.3	Statistical results for broiler chickens.	38
3.4	Statistical results of activity index, weight and body surface of broiler chickens.	38
3.5	Statistical relationship between gait scores and activity.	39
4.1	Overview of chickens used in the experiments.	50
4.2	Dynamic variables extracted from the video sequence of the chickens and their description.	51
4.3	Correctly classified lying behaviour using image analysis.	54
4.4	NoL and LTL of broiler chickens with different gait scores.	55
5.1	Accuracy results for the proposed algorithm.	68
5.2	Number of pecking, feed uptake feed loss and feed intake of chickens.	69
6.1	Accuracy results for the proposed algorithm.	82

Chapter 1

General Introduction

1.1 Modern livestock

1.1.1 Importance in the world

Animal products (meat, eggs, milk) are important components of modern worldwide food production. The world population reached over 7.1 billion people in 2013 and income levels have risen in some developing countries such as China, India and Brazil, creating a huge demand for more food production. As a consequence, the consumption of meat and other animal products has grown considerably. As Table 1.1 shows, in 2012 meat production levels had risen sharply compared with production in 1961, with pig meat up by 441%, beef and buffalo meat up by 233%, eggs up by 476%, poultry meat up by 1180%, milk up by 219% and sheep and goat meat up by 228%. This year, over 60 billion animals will be slaughtered for food production. Livestock production is going through major changes in order to satisfy this enormous demand for animal products (see Figure 1.1).

Feeding the world with high-quality, assured food is an important concern for the food supply chain. As poor countries make the transition from a plant-based diet to a meat-based diet, the consumption of meat and other animal products has grown significantly worldwide. According to the global statistics, meat and other animal foods are fairly income elastic.

Table 1.1: Changes in global livestock production (FAO 2012).

	Production (million tonnes)			Production per person (kg)		
	1961	2012	2012/1961	1961	2012	2012/1961
Pig meat	24.75	109.12	441%	8.25	15.59	189%
Beef and buffalo meat	28.76	66.89	233%	9.59	9.56	100%
Eggs	15.11	71.92	476%	5.04	10.27	204%
Poultry meat	8.95	105.64	1180%	2.98	15.09	506%
Milk	344.18	753.93	219%	114.73	107.70	94%
Sheep and goat meat	6.03	13.77	228%	2.01	1.97	98%

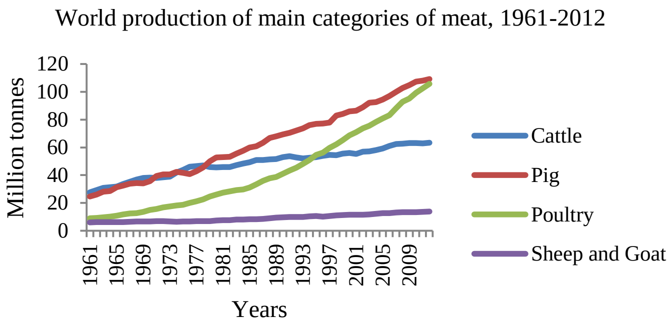

Figure 1.1: World production of main categories of meat from 1961 to 2012 (FAO 2012).

As countries become wealthier and the world's population continues to increase, income levels have risen and there has been a trend towards urbanisation. Consequently, demand for meat and other livestock products have grown radically, according to the Food and Agriculture Organisation (FAO, see Figure 1.1). The changes in the production of poultry and pig meat in BRIC countries can be seen in Figure 1.2. The big challenge for livestock in the future is that worldwide meat production is expected to increase by 40 percent over the next 15 years (FAO 2009). To feed the expected world population of 9 billion people, food production must increase by about 70 percent compared with its current level by 2050 (FAO 2009). This estimated population increase is expected to bring a rise in annual meat consumption (200 million metric tons) (Floros 2008).

Gross domestic product (GDP) per head has been growing in most regions of the world. Between 1990 and 2008, it rose by 219 percent worldwide and by 207 percent in low-income countries (FAO 2010). According to the FAO, in China GDP per head grew by over 1000 percent from 1990 to 2005 (FAO 2010). Meat consumption rose from 26 to 54 kg, milk from 7 to 26 kg, and eggs from 17 to 19 kg per head in a year (FAO 2010). According to the FAO, global meat production was 200 million metric tons in 1999 and a 25% increase is expected by 2015. Furthermore, world food production is expected to increase by 62% in the next 17 years. The highest increase in those 17 years will be in meat (42%). As a result of this higher demand for meat products, EU and global animal food production is dealing with health and welfare problems in livestock reared on an industrial scale. As the FAO states, it is clear that the world will have to adopt some novel technologies for intensive animal food production systems (FAO 2007). In this area, the potential for combining novel technologies with biology offers a large number of opportunities for livestock management in the EU.

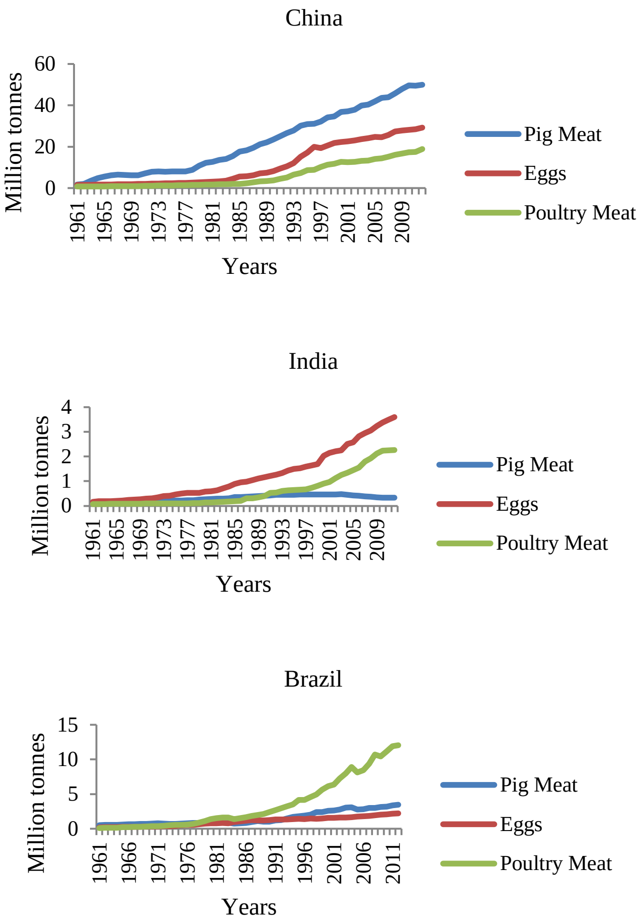

Figure 1.2: Production of poultry and pig meat in BRIC countries (China, India and Brazil) from 1961 to 2012 (FAO 2012).

1.2 Problems

1.2.1 Productivity

Several measures can be used to evaluate the productivity of a flock of broilers; these include growth rate, days to market, mortality and feed efficiency. Feed is typically the most costly expense in broiler production. As a result, feed efficiency is typically the primary tool by which a flock is evaluated. Many factors affect both growth rate and feed intake, and thus affect feed efficiency. However, house temperature, litter quality, feed wastage and feed deprivation, diseases, culling and human factors can affect broiler productivity (Anonymous 2008). For example, placing too much feed in the bird feeders causes feed wastage and results in higher feed conversion. To prevent excessive loss of feed, the feeding behaviour of chickens can be continuously monitored by means of a sound-based technology and specified quantities of feed can be added to the feeder by running the automated system on the basis of the dynamic information coming from the monitoring tool.

The intensive methods currently used in poultry production aim to use the latest technological solutions to maximise the profits from bird productivity. However, these methods do not always fulfill the natural needs of animals and result in low welfare levels (Sanotra et al. 2001). Bird behaviour is the most critical indicator of welfare, together with the results of production (Dawkins 1999; Duncan 2002).

However, according to Linder and Sanotra the quality of management systems is the best way to manage avian welfare; production results are less suitable as they are often affected by welfare levels (Linder and Hoy 2005; Sanotra et al. 2001). Poor management conditions increase leg problems and are usually harmful to health, which has a direct effect on bird behaviour and productivity (Sanotra et al. 2001). This affects some behaviours, such as locomotion, feed intake, water intake and lying, and as a result birds are unable to fulfill their basic needs (Sosnowka and Muchacka 2005).

1.2.2 Environmental impact

The population growth in the world and economic growth in developing countries are expected to produce more and more demand for animal products such as meat, milk and eggs (FAO 2009). Thus, increasing livestock production in an environmentally and economically sustainable manner needs to be a priority for animal agriculture, and is linked with global food security.

Global food security depends on new technologies which will improve livestock production while adapting to and minimising climate change and protecting crops and ecosystems from the threat of pests and diseases. It also requires improvements in the nutritional quality and safety of food products for humans. However, livestock production is the primary tool for economic development. Thus, new technologies can improve livestock production while minimising environmental impacts, and can also improve natural resource management as a means of ensuring the health and safety of humans (Krehbiel 2013).

Today’s technologies can enormously reduce the excretion of nutrients by animals, and as a consequence the land mass needed for the nutrients is reduced. Dietary strategies are a perfect method of limiting the potential for environmental pollution and generating an equal balance between imported and exported feed. Precision feeding can greatly reduce nutrient excretion, and therefore reduces the concentration of nutrients in manure. However, excretion and manure composition can be affected by animal management and health. The quantities of nutrients in the waste stream can be reduced by controlling feed wastage. Maximising flock health can improve the efficiency of nutrient conversion into animal products such as meat, milk and eggs. Biosecurity procedures adopted under PLF will not only increase animal productivity, but also will reduce feed costs and nutrient excretion by limiting the introduction of new disease to the farm and providing measures to control or eliminate the spread of disease (Carter and Kim 2013).

Livestock have a major impact on waste recycling. For example, distillers dried grains with solubles (DDGSs), a by-product of biofuel production, can be used in animal feed instead of grain. This helps to maintain the nutrient balance and improve the economics of biofuel production (FAO 2009).

There is still some discussion about the use of feed grain for livestock feed. Whereas livestock can convert feed grains and roughage into food for human consumption, non-ruminant animals such as broilers are fed large amounts of grain because they cannot use much roughage (James and Frank 2008). However, poultry feeds contain approximately 30% fish meal, meat and bone meal which are by-products of milling and fermentation. These feeds cannot normally be used directly in human foods (James and Frank 2008). However, ruminants can convert large quantities of materials like stems of major cereals which cannot be used directly for human food. Almost half of the chemical energy in corn, wheat and rice is found in the stems of the plant, which cannot be used directly by humans for food. Ruminants convert these crop residues into human food.

Based on the global statistics, there will be an increasing demand for animal products in the future. If we are to balance animal productivity with nutrient output, producers, nutritionists and waste management specialists need to take concerted action to reduce the risks associated with animal wastes (Carter and Kim 2013). Methods of improving the efficiency of livestock production include developing new breeds which are better adapted to particular production niches while dealing with climate change and water stress in order to manage water more efficiently. Environmental damage can be reduced by developing innovative animal health systems and recycling waste, all of which requires new knowledge and technology (FAO 2011).

Further opportunities to reduce environmental impact (Capper 2011).

1. Reduce time to reach target weights.
2. Increase growth rate and feed efficiency.
3. Use broiler performance technologies.
4. Optimise diet formulation.
5. Minimise losses within the system.
6. Reduce morbidity and mortality.
7. Reduce parasite infection.
8. Improve reproductive efficiency.
9. Increase the carrying capacity of land.
10. Improved pastures.
11. Better forage varieties.
12. Reduce post-harvest resource use and emissions.
13. Water, paper, plastics, styrofoam

1.2.3 Animal health and welfare

Since the 1970s, consumers have become more aware of the effects of increases in scale and related welfare problems in the animal production industry. Together with this, most producers of animal products have used some specific arguments about health and welfare standards. Modern animal production has become more concentrated through the use of more productive livestock breeds (Otte et al. 2007). At the same time, farm size has increased. For example, in Denmark, the United Kingdom, the Netherlands, France, Belgium and Spain more than 70% of specialised pig farms now comprise more than 1000 animals in each unit. Similarly, in most of these countries, the average herd size is more than 100 dairy cattle (Windhorst 2004). Concurrently, the number of animals per stockman has increased considerably due to mechanisation and changes in housing systems. Whereas in the 1960s a full-time stockman cared for about 20 sows or cows, he is now expected to look after five or ten times this number. Although the size of poultry houses has not changed much over the past 20 years, the number of animals for which a stockman is responsible has increased steadily, along with stocking densities which, in broiler production, have risen from 15 to over 35 kg per m^2.

As a consequence of this growth in animal population, there is a need to develop new methods of measuring and monitoring livestock health and welfare, to use them to control production quality, and to certificate farms which comply with health and welfare requirements. Farmers cannot monitor 1000 animals using their eyes and ears alone. Unfortunately animals and their welfare might become a secondary consideration in an open and competitive market where the main driver is the profitability of the enterprise. It is now clear that productivity and profitability should not be the only criteria by which an enterprise is managed and that animal health and welfare are important too. Thus, several countries have set up governmental committees such as the Brambell Committee in the United Kingdom and the Husbandry and Animal Welfare Committee in the Netherlands to investigate the welfare of intensively housed livestock (Brambell 1965; Anonymous 1975).

Rearing livestock for humans raises a new issue in the discussion of the relationship between humans and animals, namely the status of animals and obligations of people (Francione 2008). Animals under human care should be treated well and should not suffer unnecessarily. Animal welfare is based on an interpretation of scientific studies of farming practices. By contrast, 'animal rights' usually views livestock rearing as exploitation regardless of the farming practice used (Francione 2008).

Animal welfare science is a relatively young discipline which addresses the welfare status from the animal's point of view (Anonymous 2001). Unfortunately, we cannot ask animals how they feel, and there is no one single instrument (or simple gold standard) which enables us to measure the animal welfare status directly, so we try to infer this from measurable indices that we know or supposed to be related to animal welfare status. There is a big scientific debate on how to define animal welfare. At one end of the spectrum are definitions which refer directly to measurable parameters of biological functioning such as survival, normal behaviour and physiology, and reproductive success. For example, Broom (1986) defined animal welfare as the status of an animal as regards its attempts to cope with its environment. Duncan defines animal welfare in terms of 'five freedoms' which were set out by the UK Farm Animal Welfare Council (FAWC) and determine the ideal states for acceptable welfare (Duncan 1996). These freedoms are: freedom from thirst, hunger and malnutrition; freedom from discomfort; freedom from pain, injury and disease; freedom to express normal behaviour; and, finally, freedom from fear and distress (FAWC 1993). The Farm Animal Welfare Council (FAWC) in the UK also makes the following statement about an animal's quality of life: 'Animals should have a life worth living' (FAWC 2009). FAWC says that if the evidence is inconclusive, the animal should be given the benefit of the doubt (FAWC 2009). According to the Farm Animal Welfare Council, there are 'iceberg' indicators of animal welfare that provide an overall assessment of welfare. Many measures of welfare are effectively summarised and easy to understand, for example, ease of movement and absence of prolonged hunger.

Unfortunately there is still discussion about a single definition of welfare among scientists, farmers and others. Some scientists say that the term ‘health’ is encompassed by the term ‘welfare’ (Broom 1986; Fraser and Leonard 1993; Broom and Johnson 2000). Health is usually considered to be a part of welfare and therefore disease always has some harmful effect on welfare. According to Broom, the word ‘health’, like ‘welfare’, refers to the state of the body system and can be described as ‘good’ or ‘poor’ (Broom and Corke 2002). When the health of an animal is poor, its welfare is also poor, but poor welfare does not always indicate poor health. An assessment system based on animal measures was developed by Welfare Quality (a European project) for three livestock species. They assessed farm animal welfare on farms and in slaughterhouses in a standardised way by assigning it to one of four categories (from poor to excellent animal welfare) using a science-based methodology.

Animal-based indicators are needed in order to determine whether welfare objectives have actually been met. Welfare measurements should be based on knowledge of the species biology (WQ 2009). When animal welfare is compared in different situations, it must be assessed in an objective way. Welfare Quality combines analysis of consumer perceptions and attitudes with existing knowledge and expert opinion from animal welfare science.

Welfare Quality then sets out to develop reliable and feasible measures to assess the welfare level of farms and slaughterhouses. Animal-based measures are used to estimate the actual welfare state of the animals in terms of their behaviour, fearfulness, health or physical condition (WQ 2009). Animal-based indicators include variables such as body condition, abnormal behaviour and skin lesions, which are measured on the animal itself. For this reason, assessors go into the field to carry out manual observations of animal welfare based on the protocols developed (WQ 2009). To eliminate subjectivity (results might vary depending on the observer’s mood), measures are regularly tested for inter-observer (between different observers) and intra-observer (within the same observer) reliability. The testing procedures are also standardised to allow comparisons between measures (WQ 2009).

Since subjectivity can be resolved statistically, the biggest difficulties facing application of the existing Welfare Quality protocols lie in the time, costs and effort needed for a complete assessment on the farm and in the fact that it is only a momentaneous score. A complete assessment on just one day of a year easily costs 1500 euro. This is expensive for a farmer, especially as the situation might have changed on the following day, for example due to changing weather conditions.

In traditional methods (Laca and Vries 2000; Clapham et al. 2005), sensors must be attached to and/or injected into the animal. This has some disadvantages, e.g. the animal may be influenced by the sensor and the animal response may be affected; the sensor may be lost due to migration within the body; hygiene issues; each animal has to wear a sensor but a big broiler house, for instance, contains more than 150,000 chickens per growing period which means that 150,000 sensors are needed and the sensor cost has to be calculated per individual.

By contrast to the welfare quality approach where farms are scored once a year to check their animal welfare status, the concept of Precision Livestock Farming (PLF) is to implement a management system for the farmer. This PLF system uses technology to continuously monitor and improve the welfare, health, productivity and environmental impact of the animals. The advantage of this approach is that it operates continuously day and night, is fully automated and consequently cheaper, and is part of a real-time management system which aims to improve conditions for the animals and the farmer. The conditions for both animals and farmer can be improved by automating some measures using modern technology, based on sensors, sensing systems (image, sound, etc.) and real-time modelling. The general aim is to achieve continuous assessment of livestock status by continuously measuring the health, welfare and performance of these animals and taking the results into account immediately in the management system. Automated recording of animal-based parameters has a number of potential advantages over on-farm scoring. Firstly, automated recording is less time-consuming than on-farm auditing. Secondly, recordings can be made in real time, on a more continuous basis. Thirdly, information can be managed using databases and web-based information exchange methods, which reduces the need to send specialised personnel out to farms. Fourthly, existing variables such as body temperature, skin lesions and animal activity can be measured more objectively. Fifthly, automated recording may enable new variables, such as heart rate (variability), to be incorporated into the welfare assessment scheme. Finally, automated recording may overcome some of the methodological problems, such as animal disturbance and biosecurity risks, which are associated with farm visits. Essentially, automated recording may improve the repeatability and feasibility of large-scale assessment and ultimately reduce costs.

1.3 General method: precision livestock farming (PLF).

In the past, livestock management decisions have been based on the farmer’s observations and judgment. However, because of the increasing scale of farms and the high number of animals, farmers have a very high technical, organisational and logistical workload. Thus, the farmer has limited time available to monitor his animals himself. As a result, automated monitoring and control techniques are becoming more important nowadays to support management by the farmer. Precision Livestock Farming (PLF) is a tool for management of livestock farming by means of automatic, real-time monitoring/control of livestock production, reproduction, health and welfare and of environmental impacts (Berckmans 2013). PLF plays an important role in the early detection of disease and objectively assesses animal welfare in modern livestock production (Berckmans 2013). One of the objectives of PLF is to develop on-line tools for continuous, fully automatic monitoring of farm animals without imposing additional stress on the animals (Berckmans 2013). The aim of these technical tools is not to replace the farmer and the vet but to support them as they cannot watch the animals 24 hours a day for 7 days a week. PLF provides unlimited observation time, because computers do not get tired and, besides, the technical tools are becoming cheaper.

The general goal is to obtain a full picture of animal status and the animal environment on a continuous basis, focusing on animal health, behaviour and performance (Berckmans and Guarino 2008). Figure 1.4 shows the basis of PLF for monitoring biological processes and physical processes (Aerts et al. 2003; Wathes et al. 2008). Precision Livestock Farming covers the measurement, prediction and data analysis of animal variables. PLF also offers new possibilities for continuous, automatic collection and analysis of data from farm animals (Berckmans 2004). This technology will make it possible to improve food safety and quality and to achieve efficient and sustainable livestock farming, healthy animals, and an acceptable environmental impact from livestock production (Berckmans 2004).

PLF consists of measuring variables on the animals, modelling these data to select information, and then using these models in real time for monitoring and control purposes (Berckmans and Guarino 2008). PLF offers huge potential to develop this technology for continuous automated monitoring and control of animal health and welfare. Applications of PLF make it possible to use knowledge and information in the monitoring and control of processes (Berckmans and Guarino 2008).

The PLF approach applies to animal growth, behaviour and products, some diseases, and the physical environment of a livestock building (Wathes et al. 2008). For good livestock management, the PLF approach makes use of modern monitoring and control theory. Three conditions must be satisfied in order to achieve efficient monitoring and control of such processes.

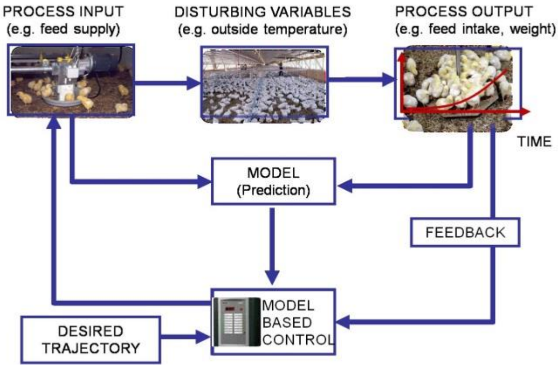

Figure 1.3: Schematic overview of PLF to control biological processes such as animal behaviour, physiology and growth (Aerts et al, 2003)

The first condition to be satisfied is that animal variables including weight, activity, behaviour, drinking and feeding behaviour, and physiological variables such as body temperature and respiration frequency must be continuously measured and monitored. The second condition that must be met for accurate analysing and management is that a reliable prediction of changes in animal variables and animal response to various environmental factors must be available. The third condition to be satisfied is that this prediction and on-line measurements must be integrated into an on-line analysis algorithm for automatic monitoring or management of the animals or to control actions such as climate or feeding.

1.3.1 PLF technology

Technology is becoming cheaper all the time, consumes less energy and improves the potential for monitoring of various biological processes in real time. Alongside the increase in technological possibilities, there has been an increase in biological understanding of systems. In this thesis we refer to biological systems. These are systems in which the crucial part of the process is a living organism, e.g. plants, in which photosynthesis is a response to light (Boonen et al. 2002), animals, in which the body weight depends on food intake (Aerts et al. 2003), or humans whose heart rate varies with power input during treadmill training (Lefever et al. 2010). When we consider biological systems as defined above, we can see that they react to their environment or change a process within the body itself in a specific way. In biological systems, this reaction or change in a quantitative variable is known as the bio-response. In conclusion, a bio-response may be defined as a quantitative measurable variable of a monitored biological process. This response may be caused by a change in its environment, its physiological status or its mental state. Physiological status reflects the health status; for example, a lame chick will start lying down because of a problem with its legs. The reason why it is important to quantify the dynamics of a biological system is that once you know how a system reacts, you can anticipate what it will do. For example, the calculated activity of broiler chickens can be linked to lameness.

1.3.2 Sensors and sensing.

The most important benefit provided by technology in livestock production is the development of sensors and sensing systems to automatically monitor and evaluate data in real time (Berckmans 2008). It is now possible to gather data from livestock using innovative, low-cost IT systems which can be integrated by using knowledge-based computer models in real time (Berckmans 2004; Berckmans and Guarino 2008; Banhazi and Black 2009). Stockmen routinely collect auditory, olfactory and visual information to evaluate animal health, welfare and productivity. New technology can aid this task, even with large flocks or herds, by using sensors and sensing techniques (Berckmans and Guarino 2004).

A sensor is a technological device that is positioned in or on the body of the biological organism, whereas a sensing technique is a measuring technique that does not touch the animal and records signals from a distance (Cangar 2011).For example a polar heart rate monitor is a sensor, while a feeding behaviour detection system using a microphone is a sensing technique. Sensing systems which monitor feeding times, feed intake, animal health and behaviour are under development. With these systems measurement of conventional performance parameters such as real-time, on-line analysis of sounds, images, live weight, etc. is becoming feasible (Wathes et al. 2008).

For example, low-cost cameras and image analysis techniques can be used to quantify animal behaviour (Leroy et al. 2004) or to estimate the size, shape and weight of farm animals (e.g. pigs: White et al. 2004; broilers: Chedad et al. 2003). Animal sounds can also be monitored and evaluated in order to assess health status (VanHirtum and Berckmans 2004). Automatic weighing systems for poultry have been used to predict the average flock weight (Vranken et al. 2004). Sensors for quantifying milk conductivity and yield of individual cows are available and can be used to provide early detection of poor welfare (Kohler and Kaufmann 2003). The above examples are not exhaustive, but indicate the present and future possibilities in monitoring animal health, welfare and productivity. The advantage of these systems is that a lot of information can be gathered without subjecting animals to additional stress (Hamilton et al. 2004).

1.4 Hypotheses and objectives

This thesis describes new methods of Precision Livestock Farming to evaluate animal welfare, and focuses on monitoring of broiler behaviour using image and sound analysis instead of the traditional visual observation methods.

The general objective of this thesis is to investigate whether technology can assist the eyes and ears of a farmer in large groups of broilers. We assume that algorithms from image and sound analysis can be implemented in real time and used continuously over a variety of assessments to extract information about the physiological and behavioural status of the monitored broiler chickens. Two hypotheses are formulated:

Hypothesis 1: "A fully automated continuous monitoring system based on vision technology can be used to determine the lameness score of broiler chickens by assessing differences in biological status such as activity, exploration, locomotion and posture behaviours. In this case the continuous image recordings hold information about the biological status of an individual and group of broiler chickens."

Hypothesis 2: ""By automatic recording of pecking sounds from broilers, it is possible to measure feed uptake of chickens in real time. The pecking sound detection tool is a cheap and accurate way of measuring feed uptake and calculating the feed wastage and feed intake of broilers in commercial farm conditions."

To test these hypotheses, two objectives were formulated. The first objective was to assess the feasibility of extracting physiological and behavioural information from a group of broilers during growth, taking only image information into account. More specifically, automatic image monitoring systems to measure the activity, exploration, locomotion and posture behaviours of broiler chickens in relation to their lameness degree (gait scores) were implemented. The second objective was to examine the feasibility of assessing the eating behaviour of broiler chickens, taking only the feed intake information into account. More specifically, a fully automated sound monitoring system was developed to measure the feed uptake, feed wastage and feed intake of broilers. The overall aim was to prove the potential of PLF techniques for continuous monitoring of welfare and health-related responses of broiler chickens. Monitoring of health and welfare in broilers is explored in this thesis by means of various assessments, from chicken activity and use of space, through bird locomotion behaviour and body posture parameters to automatic measurement of feed intake and dynamic feeding behaviour.

1.5 Main framework of this thesis.

The methods used in this thesis are image and sound analysis to evaluate the health and welfare of broiler chickens, via real-time algorithms. In the context of healthy animals, image and sound are used as a tool for monitoring the status of broiler chickens.

Moving from a group approach, where groups of broilers are monitored, to an individual approach, the importance of individual monitoring is illustrated using chicken locomotion and posture behaviour based on images, and feeding behaviour based on feed intake, measured automatically and continuously by pecking sound detection. The same, relatively simple, analysis techniques are applied to broiler feeding behaviour, and a novel way of considering the dynamics of pecking sounds is described, making a link with feed intake.

It has been mentioned that the dynamics of pecking sounds might reflect information about feed uptake, feed wastage, meal duration and number of meals but a non-invasive sound measurement technique for objective quantification of feeding behaviour dynamics in relation to welfare has never been described before in the literature.

In order to implement real-time algorithms, they must be as simple as possible, must be user defined and information must be extracted. Because these algorithms are simple, they can be applied to broiler chickens in real time at individual or group level, depending on the context of the application. As individual birds have their own specific way of reacting to their environment, using group averages to extract information is not always encouraged as every individual bird reacts in a different way. To increase the accuracy of monitoring, individual broilers must be followed in time and specific variables must be selected that can be linked to a specific condition. Here, the role of intra- and inter-subject variability is of great importance in the interpretation of the results. The selected variables may also be specific to one individual.

Europe leads the world in research and development on livestock technology. It is evident that the use of modern information technology plays a crucial role in the early detection of disease and assessment of welfare in modern livestock production. IT systems will complement the skills of the farmer, veterinarian and inspector. By using this technology, farmers and veterinarians can continuously and automatically collect information and manage it to show citizens that livestock production is safe, humane and environmentally sustainable.

1.6 Link with other chapters

The objective of this thesis is to show that Precision Livestock Techniques are suitable for monitoring health and welfare related responses of broiler chickens. Chapters 2 to 6 describe how broiler responses were monitored using image and sound techniques.

The discussion section evaluates the results from all the chapters and discusses the potential for applying Precision Livestock Techniques to the monitoring of health and welfare related responses of broiler chickens. Finally, conclusions are drawn from the entire work. The contributions of the thesis are summarised and the outlook for future research is assessed.

Lameness is one of the most serious welfare problems affecting broilers. Waiting until the birds are slaughtered is not an ideal way of monitoring welfare because the problem cannot be anticipated at a sufficiently early stage. Real-time monitoring techniques are needed in order to detect the problem in good time. Chapter 2 therefore describes how a fully automatic monitoring and image analysis system is applied to determine the average activity levels of broiler chickens in relation to their gait scores.

Chapter 2

Application of a fully-automatic analysis tool to assess the activity of broiler chickens with different gait scores

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2.1. Introduction

The most important question relating to broilers welfare which has arisen in the last two decades is the growing susceptibility of chickens to metabolic and locomotion problems due to fast growth rates and inactivity. The SCAHAW Report says that leg disorders are a major cause of poor welfare in broilers (SCAHAW 2007). In Denmark, it has been found that over 30% of the broilers studied were limping or severely lame. In Sweden, it has been found that 72.4% of broilers had a walking abnormality and 1 in 5 were so lame that they had some difficulty in moving around. Lameness refers to an abnormal gait caused by painful lesions of the limbs or back or to mechanical defects of the limb, and indicates a painful state and discomfort. Lameness is relevant to the assessment of welfare not only because of direct painful effects on the animal, but also because weak bones mean a poorer ability to cope with the environment and perhaps earlier death as a consequence.

In commercial farm conditions, broiler chickens show low levels of activity, particularly if they are kept at high stocking densities and during the last weeks of the growing period (Blokhuis and Haar 1990; Bizeray et al. 2002). Several studies have focused upon ways of increasing activity early in the growing period, although reducing activity is sometimes desirable, for example during depopulation (Bizeray et al. 2002; Bokkers and Koene 2003; Prayitno et al. 1997). High light intensities increased the activity of broiler chickens and reduced leg problems and mortality without affecting production (Cherry and Barwick 1962). Rearing broilers in bright red light early in life increased activity and reduced leg disorders compared with broilers reared in dim blue light (Prayitno et al. 1997), whilst environmental complexity has been reported to either increase activity (Bokkers and Koene 2003) or have no effect on activity or gait score (Bizeray et al. 2002). Traditional methods of determining gait score include manual scoring of animal behaviour in the broiler house. Recorded images can also be used for manual scoring of chicken gait score. However, scoring of some animal-based information by human experts and manual methods remains difficult, time-consuming and expensive when implemented at farm level.

Image analysis technologies have been widely used in behaviour analysis of different animals. Thermal comfort behaviour of swine was analysed by Shao using programmable cameras (Shao et al. 1998). The area and perimeter of the top view of the pigs could be extracted from the images. Individual behaviour of pigs in a pen was studied by Tillett et al. (1997). In their work, an image processing technique was used to track animal movements. The fitting of a model to the top view image sequence provided data on position, rotation, bending and head nodding. The locomotion and posture behaviour of pregnant cows prior to calving was studied by Cangar et al. (2008). In their study, an automatic real-time monitoring system was used to classify specific behaviours such as standing or lying (including incidences of motion during lying), and eating or drinking. Leroy established a model-based computer vision system to study the behaviour of hens in furnished cages (Leroy, Silva, Struelens, and D. Berckmans 2005). Individual behaviours, such as standing, walking and scratching, could be recognised automatically and in real time. The use of video camera images to analyse activity is an emerging technology. It is a relatively cheap and non-invasive technique which facilitates more frequent data collection over longer time periods. A real-time analysis algorithm is used for processing and does not require large amounts of data storage. The existing image analysis tools were developed in pig and cow chambers in laboratory conditions. In commercial livestock houses, image analysis for behaviour classification becomes more complicated. Lighting, camera characteristics, background and test subject characteristics all influence the ability of the system to recognise the subject and record its movement accurately (Hoy et al. 1996). A new technique was developed by Sergeant to derive a background image representing the scene without the objects of interest and perform frame by frame image subtraction for computer visual tracking of poultry (Sergeant et al. 1998). A new hypothesis that valuable on-farm outcome measures of broiler (meat) chicken welfare can be derived from optical flow statistics of flock movements recorded on video or CCTV (closed-circuit television) inside commercial broiler houses was tested by Dawkins et al. (2009).

The objective of this study is to investigate the activity levels of broiler chickens in relation to their gait scores using an automatic image monitoring system under laboratory conditions. Furthermore, a fully automatic monitoring and image analysis system was applied to determine the average activity levels of chickens with different gait scores. The outcome of this study serves as a preliminary step for developing an automatic behaviour analysis tool for chickens with different gait scores in commercial farms.

2.2 Materials and methods

2.2.1 Birds, experimental design and video recordings

Two experiments were conducted over 5 days in two different years. In experiment 1, which took place in 2008, 14.68 hours of data were recorded. In experiment 2, which was conducted in 2009, 51.58 hours of data were recorded. The second experiment is a repetition of the first experiment except for the recording times. The experiments were conducted with Ross 308 broilers which were vaccinated against Newcastle disease (NDW, Poulvac) and infectious bronchitis (IB Primer, Poulvac) in the hatchery. On day 23, they were additionally vaccinated against Gumboro (Bursine 2, Poulvac) and Newcastle disease (Hipraviar NDV, Clone) in the broiler house, following standard procedures. For the first 9 days, a pre-starter diet with 23 percent protein and 2890 kcal AMEn/kg (apparent metabolisable energy) was given.

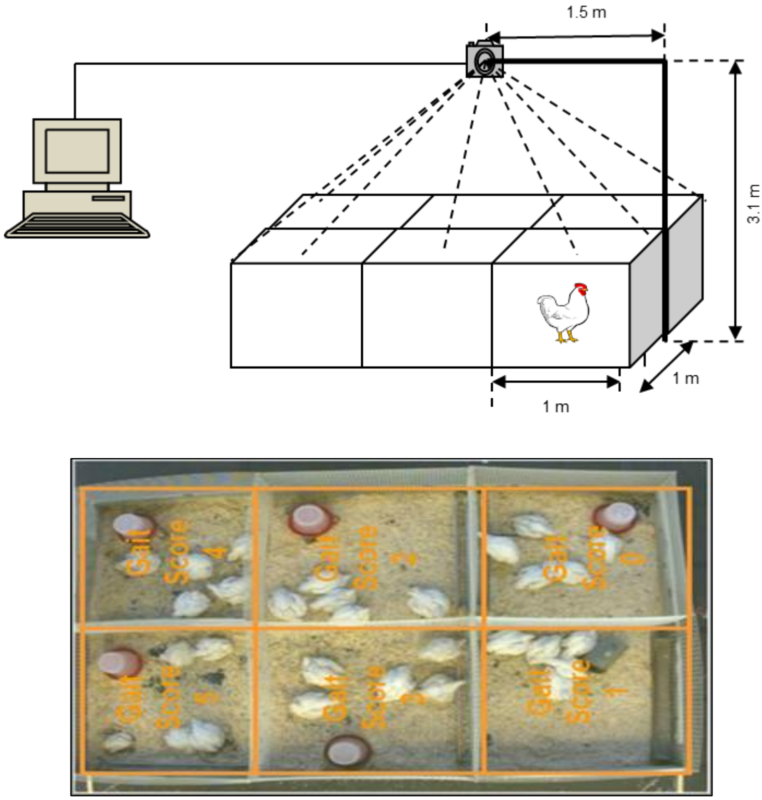

Figure 2.1: Laboratory set-up with a computer, camera and cages with five chickens in each compartment.

From day 10 until day 13, a starter diet with 22 percent protein and 2794 kcal AMEn/kg, and from day 14 to day 32, a grower diet with 20 percent protein and 2899 kcal AMEn/kg were provided. A total of 60 birds, mixed sex, 32 days old were selected from a local commercial farm (Provincial Center for Applied Poultry Research, Geel, Belgium) using the gait scoring method described by Kestin et al. (1992). Following Kestin, lameness of the chickens was ranked in increasing order from gait score zero (GS0) to gait score five (GS5), where GS0 is the healthiest (Kestin et al. 1992). The birds then were transported to the laboratory. The laboratory test installation had six stainless steel compartments (100 cm x 100 cm, width x length). The same number of mixed sex birds having the same gait score level was housed in each compartment, with a stocking density of 5 birds/m^2. Birds were kept on the floor in pens with wood shavings. Feed and water were freely available to all birds. Birds were allowed a minimum of two days to recover from the stress of transport and acclimatise to their new environment. Lights were kept on during the video recordings. A digital video camera, Guppy F036C equipped with a C30811KP 8.5 mm lens (Pentax), was mounted 4.1 m above the floor with its lens pointing downwards and directly above the centre of the six pens in order to obtain a top view of all pens in the camera image (see Figure 2.1). The camera was connected to a PC with a built-in frame grabber (E119932-U, AWM 20276, VW-1) using an IEEE 1394 fire-wire cable. Images were captured with a resolution of 1024 x 768 pixels at a sample rate of 3.5 frames per second. Video recordings were made over 5 days.

Table 2.1: Daily numbers of frames and recording times during the experiments.

Year	Exp. Day	Recording Times	No. of Frames	Year	Exp. Day	Recording Times	No. of Frames
2008	1	00:35:01	113523	2009	1	21:33:10	289796
	2	00:02:57	961		2	04:45:08	62998
	3	02:19:09	83496		3	00:56:52	14400
	4	02:46:40	961		4	20:29:54	276298
	Total	05:43:47	198941		5	02:25:37	32400
					Total	50:10:41	675892

2.2.2 Image calibration

Prior to the experiments, the image was calibrated so that the areas of pixels in the image could be converted to units of cm^2 on the pen floor. With the known dimensions of the pen (1m x 1m) and by measuring these distances in the camera pixels in units of pixels, a linear factor relating image coordinates to positions within the broiler pen could be estimated as f = 0.33 cm per pixel. Therefore, the distance between two points one pixel apart is 0.33 cm on the pen floor and the area of a region the size of one pixel is f 2 = 0.11 cm^2 on the pen floor.

2.2.3 Activity measurements

Activity of chickens with different gait scores was measured using the Eyenamic software. The software automatically grabbed 3.5 frame per second monochrome images I(x, y, t) from the camera, with I being the intensity of the pixel at coordinates (x, y) in that image. The difference between the intensity values and those of the previous image I(x, y, t-1), was calculated. From this difference, the binary ‘activity image’ Ia (x, y, and t) was calculated, containing the pixels for which the intensity change exceeded a threshold: (a). The activity index ai (t) for zone Zi was calculated from the activity image Ia (x, y, t) as the fraction of moving pixels with respect to the total number of chicken area pixels (1). The activity image (Ia) area was normalised by the total area of the chickens (1) in each compartment to compare the results independently of chicken size. To eliminate errors occurring due to different bird sizes, the total amount of measured movement was normalised by dividing the average size of the birds in each pen. The threshold T1 accounted for small intensity changes due to noise, e.g. electrical noise in the coax cabling and image acquisition circuits, small lighting variations, etc. Recordings in each experiment had different background lighting conditions. Therefore the threshold value was set to 10 percent of the maximum intensity in each specific recording separately. It was determined manually by looking at the image data since no reference values from previous studies were available. The pixel area summed in the nominator and denominator of equation (b) has an accuracy of one pixel, which was equivalent to an area of 0.11 cm^2 using the camera calibration factor.

2.2.4 Statistical analysis

Friedman's Test was used to analyse the effects of gait score on birds' activity. Friedman's Test is a non-parametric test which compares the columns without the row effects. Therefore, it does not test for row or interaction effects. The sample size was reduced by cumulating 1050 measurements into one activity value for every five minutes of recording. This was done because otherwise there would have been more than 180,000 samples for each experiment and it would have been impossible to analyse them using the statistical tests described. Following the Friedman's Test, Dunn's Test was used to define the statistical differences between the gait scores. The calculations were performed using the Statistics Toolbox of Matlab (The Math Works, Massachusetts, USA).

2.3 Results

2.3.1 Activity and gait score

A fully automatic image monitoring tool was used to calculate the activity index of a total of 30 chickens divided into six groups with a different gait score. As can be seen in Figure 2.2, there is a permanent change in activity over time. No specific pattern was observed. Therefore, it was assumed that cumulative activity values over time showed the differences between the gait scores clearly, since the time series data were too noisy to interpret efficiently (see Figure 2.2). Figure 2.3 shows daily cumulative activity levels at the end of each experiment. As the recording times were not the same on each day, the cumulative activity values for chickens with different gait scores were different at the end of the experiments. By dividing the frames into five minute intervals, it was possible to compare sub-cumulative activities in both experiments with different recording times (Table 2.1).

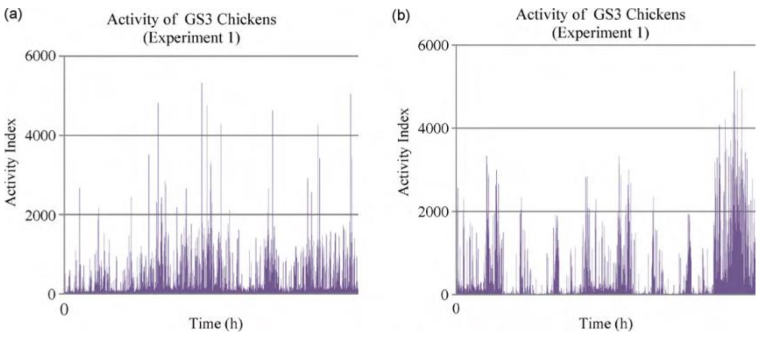

Figure 2.2: One example of continuous activity index measurement of GS3 group chickens during 3-h experiment 1 (a) and experiment 2 (b).

As can be seen in Table 2.2, the results of the Friedman's Test revealed that there is a significant relationship between the gait score and activity in both experiments (see Table 2.2, $P<0.05$).

Table 2.2: Statistical analysis of different gait scores.

First Experiment					
Source	Sum of Squ.	Deg.of Free.	Mean Squ.	Chi-Sq	P(>Chi-sq)
Gait Score	1148.90	5	229.78	328.26	0
Error	15336.10	4705	3.26		
Total	16485	5651			
Second Experiment					
Source	Sum of Squ.	Deg.of Free.	Mean Squ.	Chi-Sq	P(>Chi-sq)
Gait Score	2324.53	5	464.91	664.15	0
Error	8700.47	3145	2.77		
Total	11025	3779			

As shown in Table 2.3, activity of GS3 (mean standard deviation) was significantly higher than the other gait score groups in the first experiment (4.82±3.40), contrary to our expectations.

Although there is an overall correlation between activity score and gait score, this was not linear and GS3 has the highest activity. Table 2.3 shows that there is no significant difference between GS0, GS1, GS2 and GS4 (see Figure 2.3a).

Table 2.3. Statistical analysis of the activity index, weight and body area of broiler chickens

	Activity Index		Weight (kg)		Body Area (cm2)	
	Exp. 1 ($x10^4$)	Exp. 2 ($x10^5$)	Exp. 1	Exp. 2	Exp. 1	Exp. 2
GS0	1.94±1.45a	4.51±3.83a	1.16±0.28ab	1.32±0.32a	208.06±42.29ab	235.66±47.88ac
GS1	2.28±2.39a	4.27±4.07a	1.35±0.15a	1.49±0.17ab	231.79±23.37ab	209.81±21.18 ac
GS2	2.62±2.17a	5.02±4.57b	1.31±0.09a	1.67±0.12ab	280.63±16.24b	220.43±12.78 ab
GS3	4.82±3.40b	6.08±4.66b	1.45±0.05a	1.76±0.13b	307.42±19.19b	227.42± 6.81b
GS4	2.19±2.07a	1.58±1.37c	1.28±0.30a	1.27±0.30a	185.24±40.21ab	187.16±40.62c
GS5	0.98±0.90c	1.89±1.68d	0.90±0.10b	1.37±0.16ab	245.38±23.20a	160.70±15.20a

[1] Mean ± StandardDeviation

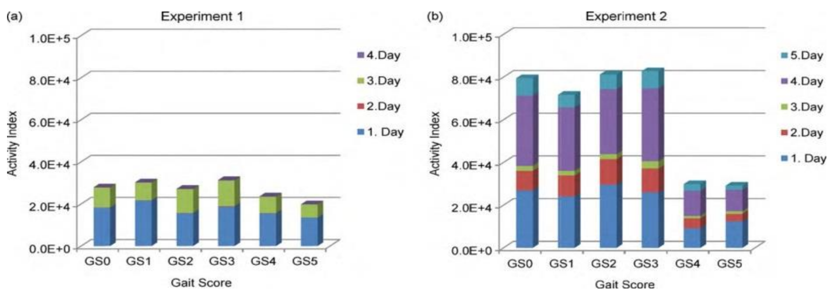

Figure 2.3: Activity index of chickens with different gait scores during experiment 1 (a) and experiment 2 (b).

The authors believe that impairment of movement of GS0 to GS3 chickens is due to their increasing weight while GS4 and GS5 are clinically sick (lame) chickens. One possible explanation for this is that GS3 chickens are bigger and heavier than the other groups (see Table 2.3); therefore they peck and fight for feed more than the other groups. In this group the broiler's need to eat was higher than the probable discomfort they might have experienced as a result of presenting an abnormal gait score. As can be seen in Figure 2.4 and Table 2.3, there was a significant correlation between bird weight and gait score, especially for lamer birds ($P<0.05$). GS3 chickens were heavier and showed the highest activity in both trials.

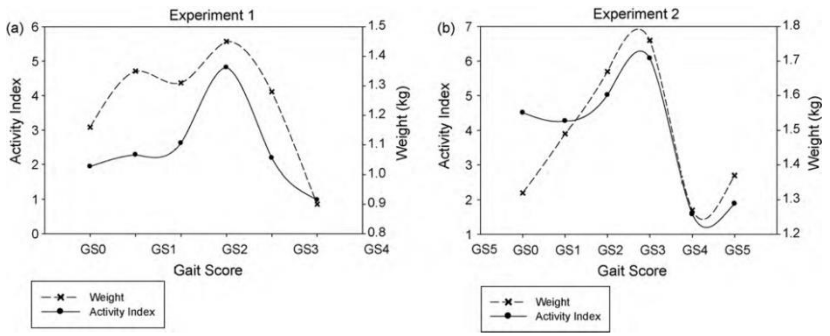

Figure 2.4: Correlation between gait scores, activity and weight of the broiler chickens.

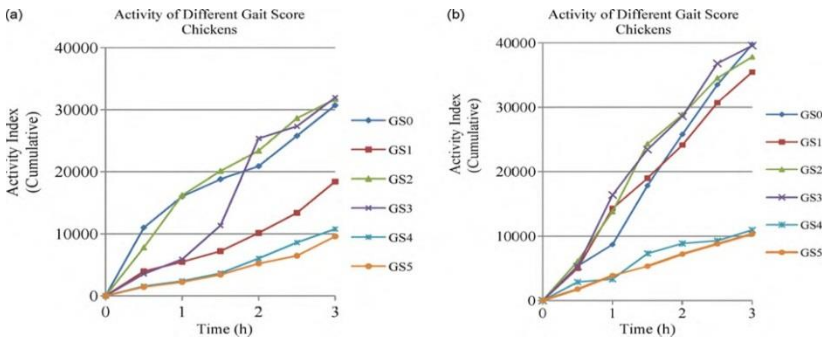

Figure 2.5: One example of the cumulative activity index of chickens with different gait scores during experiment 1 (a) and experiment 2 (b), over three hours.

GS4 and GS5 were significantly lighter and less active compared to other chickens. In the second experiment, the highest activity was again found in GS3 (6.08+/-4.66), as in the first experiment ($P<0.05$). Similar to the first experiment, GS3 chickens were again bigger and heavier (see Table 2.3). Therefore, it is assumed that they visited the feeder frequently. Moreover, GS4 (1.58+/-1.37) and GS5 (1.89+/-1.68) were found to have the lowest activity levels in the second experiment, as in the first experiment. As can be seen in Table 2.3, there was no significant difference in level of activity between GS0 and GS1 in both experiments. Cumulative activity differences between the gait scores over three hours of measurement can be seen in Figure 2.5. In particular, a significant difference in activity between GS4, GS5 and other gait scores could be seen in the second experiment; see Figure 2.5. The standard deviation in all groups was very high in both experiments. This is due to the behavioural differences between each individual bird as the same broiler breed, Ross 308, was used in both experiments. The results presented above only represent the behaviour of Ross 308, which is the most common breed in Europe. The activity index results for chickens with different gait scores may indeed be different in other breeds.

2.4 Discussion and conclusions

Studies suggest that broilers are motivated to walk long distances for feed and that their motivation can be manipulated, even within body weight groups. Accelerated growth rates and heavier body weights are known to have an influence on locomotion (Kestin et al. 2001). A heavy body weight requires more from the skeletal system which is not yet fully grown, and that leads to abnormal 'gait scores' (Corr et al. 2003). Lameness significantly changes the time budgets of much behaviour and dramatically alters feeding strategy (Weeks et al. 2000). The nature of the apparent relationship between lameness and reduced activity levels remains unclear in the literature (Hester 1994).

In this study, the relationship between gait score and activity was investigated in two experiments using 60 commercial broiler chickens reared in laboratory conditions. It was found that a significant relationship between the gait scores and activity exists ($p<0.05$). Contrary to our expectations, the relationship between activity and gait score was not linear. The GS3 birds, rather than GS0, demonstrated the highest activity level. Bokkers showed that the high body weight of broilers can be considered as a physical constraint to activity and probably to normal behaviour (Bokkers et al. 2007). However, as shown in Table 2.3, we found that the most active GS3 chickens had the highest body area (307.42+/-19.19b cm^2) during the experiments. This could be explained by the weight of the birds. As can be seen in Table 2.3, the body weights of chickens are significantly different ($P<0.05$) and the GS3 chickens had the highest body weight (1.76+/-0.13b kg). The higher activity might be explained by a higher need for feed: they need to feed more than the other birds, and they could be more active than the others because they eat more, although the feed intake of chickens was not quantified in this study. In this research it was concluded that there is a significant relationship between gait scores and activity ($p<0.05$), and more experiments are needed to determine whether the results are repeatable. This automatic monitoring of activity will allow researchers to study behaviour analysis in different gait score groups. Therefore, in the future, implementation of the proposed system should be tested in field conditions. These experiments should be repeated to investigate whether the findings of experiment 2 are consistent, i.e. that chickens with high gait scores (GS4 and GS5) exhibit significantly lower activity levels. If that is the case, this automatic activity monitoring tool can be used as an indicator of high gait scores (GS4 and GS5) in field conditions.

2.5 Link with other chapters

This chapter presents studies in which lameness in broiler chickens was automatically assessed by activity analysis of chickens at group level. For this, experts went into poultry houses and scored the animals visually. Birds with different gait score levels were then housed in different pens and the group activity of each pen was calculated using an automatic image monitoring system.

Monitoring the activity of broilers at group level was not an ideal way of assessing animal welfare because the chickens could exhibit different activity responses as a result of interactions between gait score groups of broilers while they were together, as they would be in commercial farm conditions. Therefore Chapter 3 describes studies in which all fences between the pens were removed and all gait score groups were merged into a single pen.

In Chapter 3, activity information is used to extract information about the lameness of birds, and exploration behaviour is introduced as an indicator for lameness in broiler chickens. Therefore, the activity level of broiler chickens is considered and exploration behaviour is examined. Here, information about the status of the birds as a group is not obtained on the basis of the number of pixels covered by birds; instead, a different method, namely a colour tracking technique, is developed. This is based on the idea that activity and exploration behaviour change according to the physiological status of the birds, in this particular case the lameness status. This is illustrated by considering activity and exploration behaviour in broiler chickens.

Chapter 3

Automatic identification of activity and spatial use of broiler chickens with different gait scores

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3.1 Introduction

The majority of the welfare problems today are either genetically determined, caused by housing conditions or due to the interaction of both (Bessei 2006). Lameness is a broad term which is used to describe a range of injuries to the broiler chicken of infective and non-infective origin. Losses due to skeletal disorders in broiler chickens are significant (Cook 2000). In 2002, the cost of these skeletal disorders in the USA was estimated to be between 80 and 120 million dollars per annum (Bradshaw et al. 2002). The occurrence of lameness is thought to be strongly correlated with weight and fast growth (Vestergaard and Sanotra 1999).

Moreover, locomotion problems may be painful to the animal as well as reducing their mobility and increasing secondary problems, such as hock burns, chest soiling, etc. (Weeks et al. 2000). Lameness significantly changes the time budgets of much behaviour and dramatically alters feeding strategy (Weeks et al. 2000). In commercial farms, broiler chickens show low levels of activity, particularly when they are kept at high stocking densities (42 kg/m2) and during the last weeks of the growing period (Blokhuis and Haar 1990; Bizeray et al. 2002). Several studies have focused upon ways of increasing activity early in the growing period, although reducing activity is sometimes desirable, for example, during depopulation (Bizeray et al. 2002; Bokkers and Koene 2003; Prayitno et al. 1997). 180 lx light intensity increases activity of broiler chickens and reduces leg problems and mortality without affecting production (Cherry and Barwick 1962).

Rearing broilers in bright red light in the early stages increases activity and reduces leg disorders compared with broilers reared in a dim blue light (Prayitno et al. 1997), whilst environmental complexity has been reported to either increase activity (Bokkers and Koene 2003) or have no effect on activity or gait score (Bizeray et al. 2002). Light intensity also has a significant influence on chicken activity as found by (Kristensen et al. 2006). Traditional methods of determining the gait score include the manual scoring of animal behaviour in the broiler house. However, scoring of limited animal-based information by human experts and manual methods of behaviour monitoring remain difficult, time-consuming and expensive when implemented at farm level (Kristensen et al. 2006). Compared to traditional methods, there are many potential benefits of applying image analysis technologies. Using video camera images to analyse activity is an emerging technology. It is a relatively cheap and non-invasive technique which facilitates more frequent data collection over longer time periods. If images are processed and analysed in real time, there is no need to store huge amounts of data. Machine vision technologies have been widely used in behaviour analysis of different animals. For example, individual behaviour of pigs in a pen was studied by Tillett et al.

(1997). In their study, an image processing technique was used to track animal movements. The model fit to the top view image sequence provided data on position, rotation, bending and head nodding. Thermal comfort behaviour of swine was analysed by Shao et al. (1998) using programmable cameras. The area and the perimeter of the top view of the pigs could be extracted from the images.

The existing image analysis tools were developed for pigs and cows in laboratory conditions. In commercial livestock houses, image analysis for behaviour classification becomes more complicated. Lighting, camera characteristics, background and test subject’s traits all influence the ability of the system to recognise the subject and record its movement accurately (Hoy et al. 1996). To solve this problem, a new technique was developed by (Sergeant et al. 1998) to derive a background image representing the scene without the objects of interest and perform frame by frame image subtraction for computer visual tracking of poultry. Various studies were conducted by the researchers using this method (Rajkondawar et al. 2002; Song et al. 2007; Aydin et al. 2010).

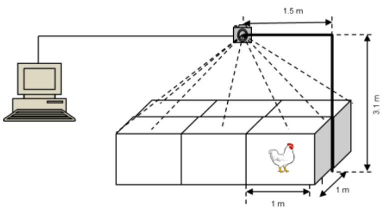
For example, Leroy established a model-based computer vision system to study the behaviour of hens in furnished cages (Leroy et al. 2006). Individual behaviours such as standing, walking and scratching could be recognised automatically and in real time. In another study, the locomotion and posture behaviour of pregnant cows prior to calving was studied by Cangar et al. (2008). In their research, an automatic real-time monitoring system was used to classify specific behaviours such as standing or lying (including incidences of motion during lying), and eating or drinking. In another study, an image analysis tool was used by Aydin et al. (2010) for automatic measurement of the activity level of broiler chickens with different gait scores. This research found that there was a significant relationship between the gait score assigned by the experts and the activity monitored by image analysis. During this study, all gait score groups were housed and monitored in separate pens throughout the experiment. Although information about the relationship between movement and space use and lameness of broilers can be found in the literature (Cherry and Barwick 1962; Prayitno et al. 1997; Weeks et al. 2000) there are no studies which describe a system for automatic measurement of the activity of broiler chickens with different degrees of lameness in two phases, which leads to the objectives of the research presented here. In the first phase, activity was measured while the chickens were housed in groups in separate pens according to their degree of lameness. In the second phase, activity and use of space was measured after all gait score groups were merged and chickens were kept in a small flock in one pen.

This advanced approach was chosen to investigate, as a first objective, whether the housing conditions in the first and second phase have an impact on the activity of chickens with different degrees of lameness or whether the measured activity under both housing conditions is similar and therefore the level of activity is indeed determined by the degree of lameness. A second objective of this study was to measure use of space by means of an automatic and objective technique in order to prove that the activity of chickens influences their use of space, hence lameness also impacts exploration and use of space by the animals.

3.2 Materials and methods

3.2.1 Experimental setup and equipment

The experimental period, totalling 12 days, was subdivided into two times six days during which two different experiments were carried out. In the first experiment (day 1-6), the laboratory test installation consisted of one stainless steel compartment (200 cm x 300 cm, width x length) (see Figure 3.1a, b) containing six pens (each 100 cm x 100 cm, width x length). In each pen, the same number of birds having the same gait score level was housed with a stocking density of five birds/m^2. In the second experiment (day 7-12), the separation fences between all pens were removed. Thus, the different chicken groups were merged into one group housed within the total area of the stainless steel compartment (200 cm x 300 cm, width x length) (see Figure 3.1c).



(a)

(b) (c)

Figure 3.1: (a) test installation, (b) integrated pens, (c) merged chickens.

Birds were kept on a floor on wood shavings. Feed and water were freely available to all birds throughout the 12-day experimental period. Lamps were kept on during the video recordings. The videos were recorded daily from 09:00 until 15:00. All pen images were captured by a

USB webcam (Logitech Webcam Pro 9000) with 3.7 mm Carl Zeiss lens mounted directly above the centre of the six pens at a height of 3.1 m above the floor and with its lens pointing downwards to give a top view of all pens (see Figure 3.1a). The images were captured with a resolution of 640 horizontal by 480 vertical pixels at a sample rate of five frames per second.

3.2.2 Birds

The experiments were conducted with Ross 308 broilers, which were vaccinated at the hatchery and on day 23 in the broiler house, following a standard procedure. For the first nine days, a pre-starter diet with 23 percent protein and 2890 kcal AMEn/kg (apparent metabolisable energy) was given. From day 10 until day 13 a starter diet with 22 percent protein and 2794 kcal AMEn/kg, and from day 14 to day 32 a grower diet with 20 percent protein and 2899 kcal AMEn/kg was provided. A total of thirty 26-day old birds were selected from a local semi-commercial farm (Provincial Center for Applied Poultry Research, Geel, Belgium). The gait scoring method described by Kestin was used to select the birds (Kestin et al. 1992).

Following Kestin, lameness of the chickens was ranked in increasing order from gait score zero (GS0) to gait score five (GS5) where GS0 is the healthiest (Kestin et al. 1992). The birds were then transported to the laboratory. Birds were allowed a minimum of two days to recover from the stress of transport and acclimatise to their new environment.

3.2.3 Experiments

Before the start of the experiments, an image of the empty compartment was taken by the camera for use as a background image in the image analysis procedure described at a later stage. Information about age, gait score and body weight of all chickens was noted at the time when the birds were selected, at the end of the first experiment and at the end of the second experiment (see Table 3.1).

The first experiment (day 1-6) was conducted to measure the activity level of chickens with different gait scores. The first experiment consisted of 36 hours of video recording distributed over six recordings on consecutive days.

The second experiment (day 7-12) was conducted to measure the activity level and use of space in the same chickens after merging them into one group of 30 birds. The second experiment consisted of 36 hours of video recording of the whole group distributed over six recordings on consecutive days.

Table 3.1: Overview of chickens used in the experiments.

Overview of Chickens			
Age in Days	Gait Scores	Sex	Weight (kg)
26	*GS*0	*M*	0.83 ± 0.16
	*GS*1	*M*	0.82 ± 0.21
	*GS*2	*M*	0.79 ± 0.16
	*GS*3	*M*	0.85 ± 0.24
	*GS*4	*M*	0.84 ± 0.24
	*GS*5	*M*	0.71 ± 0.28
32	*GS*0	*M*	1.09 ± 0.28
	*GS*1	*M*	1.23 ± 0.15
	*GS*2	*M*	1.20 ± 0.09
	*GS*3	*M*	1.33 ± 0.05
	*GS*4	*M*	1.18 ± 0.30
	*GS*5	*M*	0.87 ± 0.10
38	*GS*0	*M*	1.42 ± 0.32
	*GS*3	*M*	1.88 ± 0.15
	*GS*4	*M*	1.23 ± 0.27

Table 3.2: Video recording times and number of frames.

Year	Experimental Day	Recording Times	Number of Frames
2010	12	72:00:00	1 296 000

In order to distinguish between chickens with different gait scores after the merge, the birds were coloured with four different organic powders (green, pink, purple and black). Thus, the image analysis system was able to detect chickens belonging to a certain gait score group by applying an advanced method. The chickens in the GS0, GS3 and GS4 groups were selected for further analysis of their activity and use of space in a merged flock. Since the algorithm could detect three different colours at the same time, the most representative gait score groups were selected. GS0 was selected because this group is defined as not lame and, therefore, as the healthiest group. GS3 was chosen because this group is described as lame but there is evidence from a previous study by Aydin that GS3 chickens are the most active group (Aydin, et al. 2010). GS4 was selected because this group includes clinically lame chickens that are still able to move. In total, 72 hours of data (1,296,000 frames) were recorded, summarising 1500 frames in one data set. In total, 864 data sets per gait score group were used in the analysis of both experiments.

3.2.4 Camera calibration

Prior to the experiments, the image was calibrated so that the areas of pixels in the image could be converted to units of cm^2 on the pen floor. Given the known dimensions of the pen (1 m x 1 m) and by measuring the distances in the camera pixels in units of pixels, a linear factor relating image coordinates to positions within the broiler pen could be estimated as f = 0.33 cm per pixel. Therefore, the distance between two points one pixel apart is 0.33 cm on the pen floor. The area of a region equal to the size of one pixel is f 2 = 0.11 cm^2 on the pen floor. The camera settings for the recording were set to five frames per second to reduce the storage capacity needed for all the recorded videos.

3.2.5 Image analysis

The image analysis algorithm aimed to use simple techniques to automatically measure features of chickens in each image, taking advantage of the fixed camera setup. By combining these features over subsequent images, the pixels belonging to the surfaces of the chickens were identified. This procedure is automatically repeated for all images in each video. Additionally, after identifying the locations of chickens, the distances between the centre points of the chickens were calculated.

3.2.6 Activity calculation

In the first experiment, the ‘background’ image of the empty compartment was taken prior to the experiments using a camera which was in a fixed position during the experiments. The boundary of the chickens could therefore be estimated using the background subtraction technique. The background image was subtracted from every image I(x, y, t) taken at time t from the recorded video of the compartment/pen containing the chickens. The software automatically grabbed five frames of monochrome images per second, I(x, y, and t), with, I being the intensity of the pixel at coordinates (x, y) in that image. The difference in intensity values between two subsequent images, I(x, y, t-1), was calculated. The binary ‘activity image’ Ia (x, y, and t)was calculated from this difference and contained the pixels for which the intensity change exceeded a threshold (Leroy et al. 2006):

$$I_a(x,y,t) = \begin{cases} 1 & \text{if } I(x,y,t) - I(x,y,t-1) > \tau_1 \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

From the activity image Ia (x, y, t) the activity index ai (t) for zone Zi was calculated as the fraction of moving pixels with respect to the total number of chicken area pixels (b). Zone Zi is defined as the area of each pen in the compartment in the first experiment and the area of the whole compartment in the second experiment. During the analysis, normalisation was performed to eliminate errors occurring due to different bird sizes. The activity image (Ia) area was normalised by dividing the daily average size of the birds in each pen to compare the results independently of chicken size.

$$a_i(t) = \frac{\sum_{(x,y)\in Z_i} I_a(x,y,t)}{\sum_{(x,y)\in Z_i} b} \qquad (2)$$

The threshold t1 accounted for small intensity changes due to noise, e.g. electrical noise in the coax cabling and image acquisition circuits, small lighting variations, etc. The value of the threshold was set to 10 percent of the maximal intensity in each specific recording, as described in Aydin et al. (2010). The pixel area summed in the nominator and denominator of equation (2) has an accuracy of one pixel, which was equivalent to an area of 0.11 cm^2 using the camera calibration factor. In the second experiment, the activity of chickens with different gait scores in a merged flock was measured by an advanced method. To measure the location of the chickens, a colour filter was applied to the camera image. The three colour bands of the RGB (red-green-blue) image I(x,y) are represented by Ir(x,y), Ig(x,y) and Ib(x,y). From these colour bands, the following grey scale image was calculated, enhancing the pixels with a strong red colour component:

$$I_f = 0.7(I_r) - 0.59(I_g) - 0.11(I_b) \qquad (3).$$

This equation corresponds to the difference between the intensity of the red component and the total intensity of the image, with the latter calculated as a weighted sum of the colour components with coefficients 0.7, 0.59 and 0.11 (Leroy et al. 2009). Chickens were detected by applying a threshold (5 percent of the image intensity's dynamic range) to If (x,y,t) and calculating the mass centre (xpi, ypi) of all i = 1...n unconnected objects in the resulting binary 'chicken' image. This procedure was repeated automatically for all images within a video recording.

3.2.7 Calculation of use of space by chickens

In the second experiment, the use of space by chickens with different gait scores was investigated. Therefore, the location of the chickens (x(t), y(t)) at time t was calculated as the mass centre of Im:

$$x(t) = \frac{\sum_{x,y} x I_m(x,y,t)}{\sum_{x,y} I_m(x,y,t)}, \quad y(t) = \frac{\sum_{x,y} y I_m(x,y,t)}{\sum_{x,y} I_m(x,y,t)} \qquad (4)$$

The compartment area was divided into a grid of 640 x 480 pixels. Each mass centre of a chicken detected by the algorithm was indicated as a point in the grid. The distribution of chickens belonging to a certain gait score group was then defined by the distribution of points indicated in the grid of pixels. Each point, representing the mass centre of a chicken, proved that a certain place within the compartment had been occupied by a chicken at least once during the total daily recording time of six hours. For the assessment of use of space by chickens with different gait scores, the distribution results for the GS0 chickens were regarded as the optimal distribution and therefore set at 100 percent for each day, due to the fact that GS0 chickens are described in the literature as the healthiest chickens in terms of gait. The authors are aware that the use of space by a gait score group differs between days, but the objective of this study was to focus more on the inter gait score group variation rather than the intra gait score group variation.

3.2.8 Statistical analysis

The statistical analysis was carried out on 864 data sets per gait score group to investigate the differences in activity and use of space between the gait score groups. Friedman's test was used to analyse the effects of activity and use of space on birds' gait score. The test is a non-parametric test which compares the columns without the row effects. In the test sample, size and dependencies do not affect the test results. The sample size was reduced by cumulating 1500 measurements to one activity value for every five minutes of recordings. This was done because otherwise there would have been more than 1,296,000 samples from both experiments, and it would have been impossible to analyse them using the statistical tests described. Following the Friedman's Test, a Dunn's test was used to define the statistical differences between the gait scores. Dunn's post test compares the difference in the sum of ranks between two columns with the expected average difference (based on the number of groups and their size). The calculations were performed using the Statistics Toolbox of Matlab (The Math Works, Massachusetts, USA).

3.3 Results

3.3.1 First Experiment

A fully automatic image monitoring tool was used to calculate the activity index of a total of 30 chickens divided into six groups, each with a different gait score. As can be seen in Figure 3.2, there is a permanent change in activity over time. No specific pattern was observed. Therefore, cumulative activity values over time were regarded as clearly indicating the differences between the gait scores, since the time series data was too noisy to interpret efficiently (see Figure 3.2).

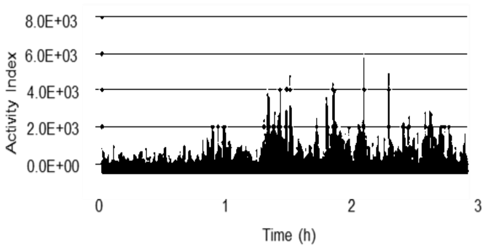
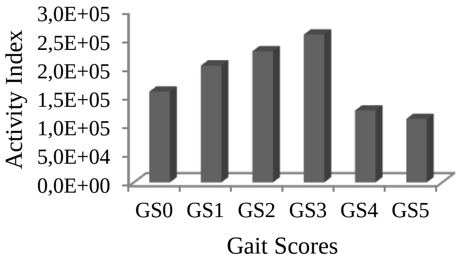


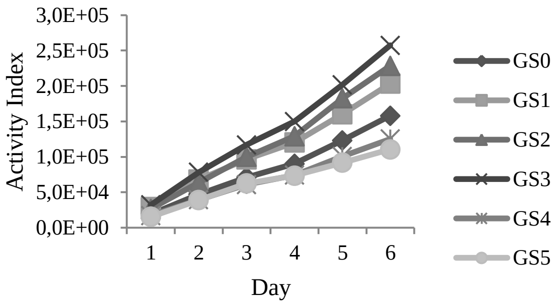
Figure 3.2. One example of continuous activity index measurement of GS3 group chickens during 3-h experiment.

Figure 3.3 shows daily cumulative activity levels at the end of each experiment. As the recording times were not the same on each day, the cumulative activity values for chickens with different gait scores were different at the end of the experiments. By dividing the frames into five-minute intervals, it was possible to compare sub-cumulative activities in both experiments with different recording times (Table 3.2).

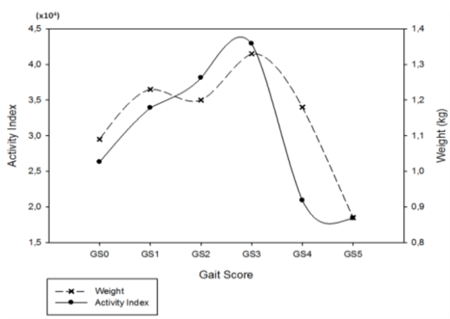
As can be seen in Table 3.3, the results of the Friedman's Test revealed that there is a significant relationship between gait score and activity in both experiments (see Table 3.3, $P<0.05$). As shown in Table 3.3, activity in GS3 (mean +/- standard deviation) was significantly higher than in the other gait score groups in the first experiment (4.82+/-3.40b), contrary to our expectations.



(a)



(b)



(c)

Figure 3.3 (a) total activity index of gait scores, (b) daily cumulative activity of all gait score groups over six measurement days, and (c) relationship among gait score, weight, and activity.

Although there is an overall correlation between activity score and gait score, this was not linear and activity levels were highest in GS3. Table 3.4 shows that there is no significant difference between GS0, GS1 and GS2 (see Figure 3.3).

Table 3.3: Statistical results for broiler chickens.

Source	Sum of Squares	Degrees of freedom	Mean Squared	Chi-sq	P(>Chi-sq)
Gait Score	97.33	5	19.47	27.81	$3.96e^{-5}$
Error	7.67	25	0.31		
Total	105	35			

The authors believe that impairment of movement in GS0 to GS3 chickens is due to their increasing weight while GS4 and GS5 are clinically sick (lame) chickens. One possible explanation for this is that GS3 chickens are bigger and heavier than the other groups (see Table 3.4); therefore they peck and fight for feed more than the other groups. In this group the broiler's need to eat was higher than the probable discomfort they might have experienced as a result of presenting an abnormal gait score. As can be seen in Figure 3.3c and Table 3.4, there was a significant correlation between bird weight and gait score, especially for lamer birds (P<0.05).

Table 3.4: Statistical results of activity index, weight and body surface of broiler chickens.

	Activity Index	Weight (kg)	Body Area (cm2)
	Exp. 3 ($x10^4$)	Exp. 3	Exp. 3
GS0	2.63 ± 2.38^{1ab}	1.09 ± 0.28^{1ab}	199.08 ± 32.24^{1ab}
GS1	3.39 ± 2.59^{ab}	1.23 ± 0.15^{a}	214.59 ± 13.57^{ab}
GS2	3.81 ± 2.56^{ac}	1.20 ± 0.09^{a}	220.63 ± 17.28^{b}
GS3	4.29 ± 3.70^{ac}	1.33 ± 0.05^{a}	234.62 ± 15.18^{b}
GS4	2.09 ± 1.64^{b}	1.18 ± 0.30^{a}	197.82 ± 30.51^{ab}
GS5	1.84 ± 1.81^{b}	0.87 ± 0.10^{b}	172.32 ± 21.10^{a}

[1] Mean ± Standard Deviation

$^{a-b-c}$ means, within a column , with no superscript in common differ significantly (P<0.05)

GS3 chickens were heavier and showed the highest activity in both trials. GS4 and GS5 were significantly lighter and less active compared to other chickens.

3.3.2 Second Experiment

In the second experiment, the color discrimination algorithm was applied to calculate the activity index and the spatial use of chickens belonging to groups GS0, GS3, and GS4 within the total group of 30 birds. This procedure was applied to the recorded data of six measurement days. The positions of the chickens were automatically detected by the color discrimination algorithm, providing the chickens' spatial use and activity within the compartment.

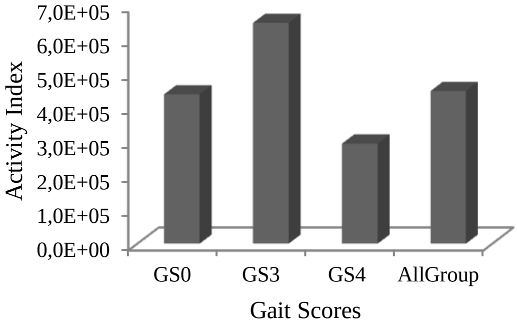
The activity results of the three different groups (GS0, GS3, and GS4) were statistically compared. The highest activity was again found for GS3 (4.14 +/-2.70), similar to the first experiment ($p < 0.05$). As the first experiment, the GS3 chickens were also larger and heavier (see Table 3.5). Therefore, it is assumed that they visited the feeder frequently. Moreover, GS4 (1.58+/-1.37c) and GS5 (1.89+/-1.68c) were found to have the lowest activity levels in the second experiment, as in the first experiment. As can be seen in Table 3.5, there was no significant difference in level of activity between GS0 and GS1 in both experiments. Cumulative activity differences between the gait scores can be seen in Figure 3.4. The spatial use of all three gait score groups (GS0, GS3, and GS4) can be seen in figure 3.5 and 3.6.

Table 3.5: Statistical relationship between gait scores and activity.

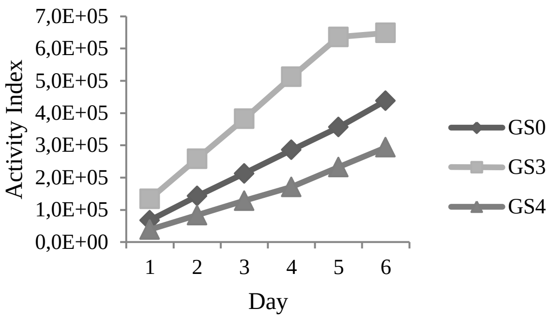
	Activity Index	Weight (kg)	Body Area (cm2)
	Exp. 3 ($x10^6$)	Exp. 3	Exp. 3
GS0	2.71 ± 1.38^{ab}	1.42 ± 0.32^{1a}	203.05 ± 34.28^{1a}
GS3	4.14 ± 2.70^{a}	1.88 ± 0.15^{b}	247.62 ± 17.08^{b}
GS4	2.16 ± 1.14^{b}	1.23 ± 0.27^{a}	199.82 ± 32.51^{a}

[1] Mean ± Standard Deviation

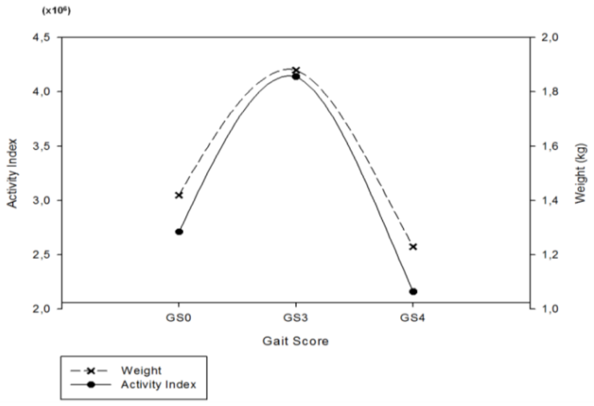
[a - b - c] means, within a column , with no superscript in common differ significantly (P<0.05)



(a)



(b)



(c)

Figure 3.4 (a) total activity index of gait scores, (b) daily cumulative activity of three gait score groups over six measurement days, and (c) relationship among gait score, weight, and activity.

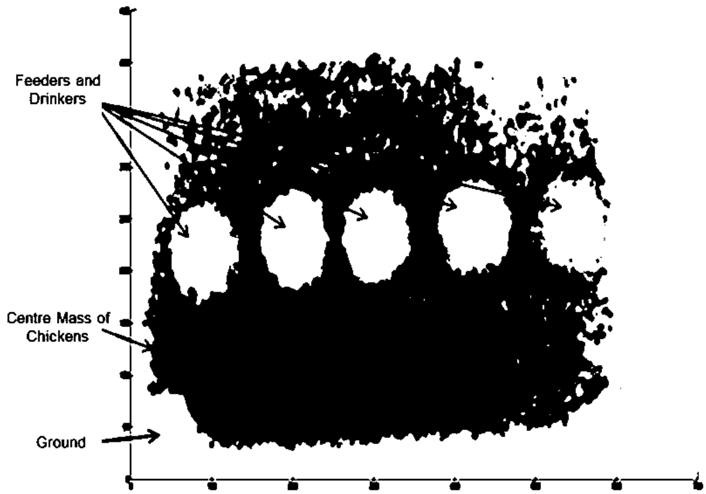


Figure 3.5: Space use pattern of the three gait score groups investigated.

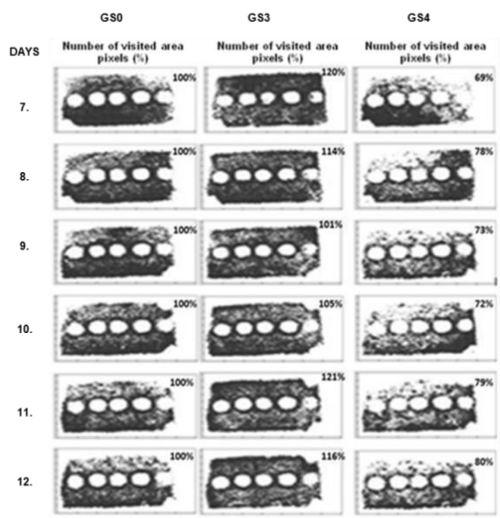


Figure 3.6 Number of areas visited by the chickens.

Significant activity differences between GS4 and other gait scores were particularly evident in the second experiment, as shown in Figure 3.4. The standard deviation in all groups was very high in both experiments. This is due to the behavioural differences in each individual bird as the same broiler breed, Ross 308, was used in both experiments. The spatial use of GS0 chickens was used as the control group, assuming an optimal use of the available space (100%), because they are defined to be the healthiest in terms of gait. Since the environment was the same for all birds, a comparison between the different gait score groups (GS0, GS3, and GS4) indicated that gait had an effect on the spatial use of the compartment area. As can be seen in figure 3.6, on each day, GS3 chickens visited between 1% and 21% more area than GS0 chickens. On the other hand, GS4 chickens visited between 20% and 31% less area than GS0 chickens. Hence, the difference between GS3 and GS4 is even more evident. GS4 chickens explored between 28% and 51% less area than GS3 chickens. The results above only represent the behaviour of Ross 308, which is the most common breed in Europe. The activity index results for chickens with different gait scores may indeed be different in other breeds.

3.4 Discussions

The activity level of chickens under two different housing conditions was investigated in two consecutive experiments using Ross 308 broiler chickens belonging to different gait score groups. The activity of chickens was calculated as the fraction of moving pixels with respect to the total number of chicken area pixels. The purpose of the first experiment, conducted by Aydin et al. (2010), was to study the activity of each gait score group. It was found that the highest activity occurred in GS3, as in the previous studies which were performed in 2008 and 2009 ($P<0.05$). As in the previous experiments, GS3 chickens were also bigger and heavier. Based on the results presented but contrary to other studies, it seems that weight and activity are related as strongly as activity and gait score. Dawkins found, by applying optical flow imaging, that poor gait scores within a flock were significantly negatively correlated with gait-related features such as percentage of time the focal birds in the video spent walking and with stride rate or how fast the birds walked (Dawkins et al. 2009).

Furthermore Bokkers showed that a high body weight (2536.0+/-31.4g) in broilers can be considered as a physical constraint to activity and probably to normal behaviour (Bokkers et al. 2007). The study presented reveals a non-linear relationship between gait score and activity. This finding confirms the results of Aydin but the question of why GS3 chickens are more active than chickens with a lower gait score remains (Aydin et al. 2010). During the first experiment, the high level of activity may be due to a high degree of competitiveness in heavy birds combined with the ability to assert themselves, particularly in the competition for food and water. This might also be a reason for more frequent pecking and fighting behaviour in GS3 chickens, as was often observed after feed was supplied. Since the birds in GS3 had the same level of physical strength and condition, they were most probably unable to build a stable hierarchy during the short period of six days, which led to aggressive interactions. In this group, the motivation to seek feed was certainly very distinct and carried more weight than any discomfort the birds might have experienced due to gait problems.

The purpose of the second experiment, performed with the same birds, was to consider whether, in a merged group, the chickens would reach the same activity levels as they exhibited within their gait score groups during the first experiment. The results obtained clearly represent the same relationship between activity levels for GS0, GS3 and GS4 as was identified in experiment one (see Figure 4b). This means that GS3 was more active than GS0 and GS4 but GS4 was less active than GS0 (see Figure 4b). Thus, the activity level is believed to be strongly related to gait as well as weight and does not alter with the change in housing conditions carried out in experiment two. The authors therefore conclude that merging the different gait score groups into one flock, combined with an increase in available space, may alter particular behaviours such as social or foraging behaviour but do not have an impact on the measurable activity levels as such. Additionally, the results strengthen the assumption that the activity of GS0 to GS3 chickens depends on their weight, which may influence the gait characteristics, while GS4 and GS5 chickens are clinically lame chickens and less able or unable to move. Also, Corr stated that heavy body weight places greater demands on the skeletal system which is not yet fully grown, resulting in abnormal gait (Corr et al. 2003). Furthermore, accelerated growth rates and heavier body weights are known to have an influence on locomotion (Kestin et al. 2001). This study investigated a very new aspect of activity and gait, namely use of space in the pen by GS0, GS3 and GS4 chickens. Based on the results, it is concluded that activity is highly correlated with use of space by the birds. It was found that GS0 and GS3 chickens explored almost the entire compartment. However, GS3 chickens always explored most space, represented as the percentage of pixels.

Some studies suggest that broilers are motivated to walk long distances for feed, which may also explain the use of space by GS3 chickens in particular (Noble et al. 1996; Bokkers et al. 2007). Chickens exhibit very distinct foraging behaviour, which usually accounts for between 50 and 90 percent of their time budget under free ranging conditions. Foraging behaviour is strongly linked to locomotion and therefore active chickens are assumed to use more space (Haas et al. 2010). On the other hand, the compartment was obviously explored less by GS4 chickens. One possible explanation might be that GS4 chickens are clinically lame, and they are not able and/or motivated to discover the entire compartment due to their lameness problem. Therefore, they remain in a certain area. In general, the results for space use reflect the activity results from the experiments. The more active chickens explored a larger area of the compartment. Although more research in this field is necessary, the authors conclude that use of space by chickens with a certain gait score is strongly related to their activity level.

3.5 Conclusions

This paper introduces a new method of assessing activity and use of space in chickens with different scores in a small flock of 30 chickens. The installation consisted of a camera system and software for automatic detection of individual chickens based on their painted colours. The results from experiment 1 in this study exactly confirm the results obtained in the previous study conducted by Aydin et al. (2010) in which GS3 achieved the highest and GS4 and GS5 the lowest activity. Furthermore, it was proven that the chickens in GS0, GS3 and GS4 exhibited the same level of activity in a small flock after all the birds were combined in one pen as they did when they were separate. Therefore, it is concluded that combining the different gait score groups into one flock may alter certain behaviours such as social or foraging behaviour but does not have an impact on the measurable activity levels. Additionally, use of space by chickens with a certain gait score seems to be strongly related to their activity level, and therefore use of space may also be a measure for activity itself. This improved automatic monitoring tool makes it possible to study activity and use of space by specific gait score groups in a small flock. For the time being, the tool is limited to applications under experimental conditions. However, the knowledge gained provides more insight into broiler behaviour in relation to gait problems, which might also, in general, be an important step towards improvements in automatic behaviour monitoring and assessment in commercial broiler houses.

3.6 Link with other chapters

Chapters 2 and 3 above discussed the assessment of lameness by automatically monitoring the activity and exploration behaviour of broiler chickens at group level. This was done in order to quantify the welfare-related behaviour of broilers in a continuous and non-invasive way in laboratory conditions.

In contrast to group level monitoring as described in earlier chapters, this chapter presents research in which birds were individually monitored using a top view camera as interactions between the birds could be different in commercial farm conditions. Furthermore, birds all live in mixed groups in a single pen on commercial farms. Therefore the research work described in the next chapter uses a different camera system which has a zoom function to capture locomotion behaviour and body posture parameters for each individual broiler chicken in order to classify specific behaviours such as standing or lying. The aim is to measure the frequency of lying and standing as a sign of gait score level due to lameness.

Chapter 4

Automatic classification of measures of lying to assess the lameness of broilers

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4.1 Introduction

The broiler chicken industry has grown steadily over the last 50 years. Genetic selection and developments in feed and management of broiler chickens have resulted in improved efficiency of broiler meat production. At the same time, public concerns with regard to the welfare of these animals have grown as well (McKay et al. 2000). The most important questions relating to broiler welfare that have been raised in the last two decades are the increasing susceptibility to metabolic and locomotion problems due to fast growth rates and inactivity of the chickens (Bauer et al. 1996; Bessei 2006). Lameness is a broad term which is used to describe a range of injuries to broiler chickens of infective and non-infective origin (Swayne and Halvorson 1991; Thorp 1994). Losses due to skeletal disorders in broiler chickens are significant (Cook 2000).

In some houses it has been observed that at least 90 per cent of chickens experienced gait problems to some extent at slaughter age (Kestin et al. 1992) and approximately 30 per cent of chickens were seriously lame. In 1998, the cost of these skeletal disorders in chickens in the USA was estimated to be between 80 and 120 million dollars per year (Bradshaw et al. 2002). The occurrence of lameness is thought to be strongly correlated with weight and growth rate (Vestergaard and Sanotra 1999). Moreover, locomotion problems may be painful to the animal and decrease their mobility while increasing secondary problems, such as hock burns and chest soiling (Weeks et al. 2000). A new method, the latency to lie down test (LTL), for assessing the severity of lameness in broiler chickens was described by Weeks et al. (2002) as the length of time that birds remained standing in shallow water. It was measured and the results were compared with the results of conventional gait scoring. There was a highly significant (P<0-001) relationship between the LTL and birds' gait scores (Weeks et al. 2002). As the original testing procedure, in which the birds are tested in groups, involves a certain settling period which makes the test too time-consuming to perform on commercial broiler farms, a new test was designed by Berg and Sanotra (2003) to record the LTL.

The main difference and/or advantage of this new test was that the birds were tested individually without visual contact with other birds and the experimental setup could be transferred between commercial farms. The results of their study also showed a clear negative correlation ($r = -0.86$, $P < 0.001$) between time spent standing and gait score. However, these types of existing test are time-consuming and the measurements cannot be performed continuously. As a consequence, there is no chance of early detection of lameness before it occurs when these manual evaluation methods are used. Furthermore, a huge amount of manpower is required, particularly to perform this type of manual test on big commercial farms with more than 100,000 chickens in a broiler house. As an alternative to these manual evaluation methods, the increasing availability of low-cost technology currently makes automated monitoring of animal behaviour feasible. Technological developments have provided a variety of tools that can be used to monitor behaviour continuously. These tools also have great potential to improve the feasibility of monitoring animal welfare indicators on-farm. Vision technology and associated image analysis, for example, allow animal movements to be assessed to a certain extent. These types of automated method have been validated against traditional methods such as manual labelling. The accuracy of measurements taken automatically varies between methods but can be increased by combining methods (Rushen et al. 2012).

Image analysis technologies have been widely used in behaviour analysis of different animals (Stuyft et al. 1991). The thermal comfort behaviour of swine was analysed by Shao et al. (1998) using programmable cameras. The area and perimeter of the top-view of pigs could be extracted from the images. Individual behaviour of pigs in a pen was studied by Tillett et al. (1997). In their work, an image processing technique was used to track animal movements. The fitting of a model to the top view image sequence provided data on position, rotation, bending and head nodding. The locomotion and posture behaviour of pregnant cows prior to calving was studied by Cangar et al. (2008). In their study, an automatic real-time monitoring system was used to classify specific behaviours such as standing or lying (including incidences of motion during lying), and eating or drinking. Leroy established a model-based computer vision system to study the behaviour of hens in furnished cages (Leroy et al. 2005). Individual behaviours such as standing, walking and scratching could be recognised automatically and in real time. Furthermore, investigating the locomotion behaviour of broiler chickens in relation to gait score can serve as a measure for lameness (Bokkers et al. 2007; Aydin et al. 2010). It is clear from the literature that using video camera images to analyse individual behaviours is an emerging technology.

A major advantage of this type of automated behaviour monitoring is that measurements can be made continuously throughout the life of a flock, they are fully automated, completely non-invasive and non-intrusive and do not involve the biosecurity risk of having people visiting different farms to perform gait scoring (Dawkins et al. 2009). The non-invasive nature of the equipment means that it can be used for long-term and continuous monitoring of animals without disturbing them. A second important advantage is that the equipment is relatively cheap. For example, relatively simple webcams were used successfully by Dawkins et al. (2009). A third important advantage is that a real-time analysis algorithm can be used for processing. Therefore, there is no need to store huge amounts of data and no further data transmission is needed. The first objective of this study is to investigate the lying behaviour of broiler chickens (the total number of lying events and the duration of the latency to lie down in broilers) in relation to their gait scores using an image-based monitoring system under laboratory conditions. By using this system, it is possible to automatically classify behaviours which are relevant to lameness assessment in broiler chickens. The second objective of this study is that it should serve as an additional method for developing an automatic lameness monitoring tool for chickens with different gait scores. By combining this method with other systems, it is possible to develop an automated lameness monitoring tool with higher accuracy. As concluded in the study of Rushen et al. (2012), these types of automatic system may be combined with other monitoring tools such as tracking the activity level of broilers (Aydin et al. 2010) and/or detecting the optical flow patterns of broilers (Dawkins et al. 2012) to assess the behaviour and welfare of broiler chickens with greater accuracy. Furthermore, it may also be applicable in on-line quantification and control of animal responses (Stuyft et al. 1991; Frost et al. 1997).

4.2 Materials and methods

4.2.1 Experimental design, video recordings and birds

The experimental setup consisted of a wooden test corridor, with dimensions 2.40 m (length) x 1.00 m (width) x 0.50 m (height). A digital video camera, Guppy F036C, equipped with a C30811KP 8.5 mm lens (Pentax) was mounted 2.0 m above the ground with its lens pointing downwards and directly above the centre of the corridor in order to give a top view of the walking area in the camera image (see Figure 4.1b). The camera was connected to a PC with a built-in frame grabber (E119932-U, AWM 20276, VW-1) using an IEEE 1394 fire-wire cable. Images were captured with a resolution of 1024 x 768 pixels at a sample rate of 3.5 frames per second. Video recordings were made during 5 experiments. A schematic overview of the complete setup and an image from the output video is presented in Figure 4.1.

Five experiments were carried out with a total of 250 broiler chickens (Ross 308) which were obtained from the Provincial Centre for Applied Poultry Research, Province of Antwerp (located in Geel, Belgium). At the start of the rearing period, the animals were treated against infectious bronchitis (IB Primer, Poulvac) and Newcastle disease (NDW, Poulvac). On day 23, the animals were vaccinated again against Gumboro (Bursine 2, Poulvac) and 'Newcastle disease' (Hipraviar NDV, Clone) in the broiler house via the drinking water. For the first 9 days, a pre-starter diet with 23 percent protein and 2890 kcal AMEn/kg (apparent metabolisable energy) was given. From day 10 until day 13 a starter diet with 22 percent protein and 2794 kcal AMEn/kg, and from day 14 to day 34 a grower diet with 20 percent protein and 2899 kcal Amen/kg were provided. During the last days, from day 35 to day 39, a 'finisher' diet was provided with 19 percent protein and 2963 kcal AMEn/kg. Drinking water was available on an ad libitum basis at all times. The chickens were scored and selected according to their degree of lameness by experts using the method developed by Kestin et al. (1992). Based on Kestin et al. (1992), lameness in the chickens was ranked by experts in increasing order from gait score zero (GS0) to gait score four (GS4) where GS0 is the healthiest. GS5 chickens were not used in the experiments as these birds are unable to walk due to the severity of lameness.

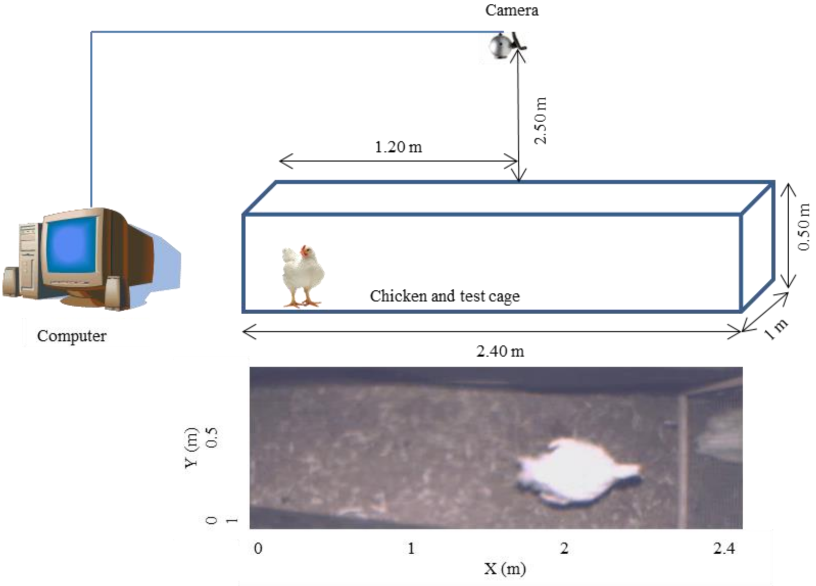

Figure 4.1: The test corridor and the video recording equipment (a), an image of the recorded video (b).

In each experiment, fifty 39-day-old broiler chickens were chosen in such a way that there were 10 samples from each gait score. Chickens were taken from a compartment of 1500 for each of the five experiments. An overview of chickens used in the experiments is presented in Table 4.1. In each experiment, a chicken was placed at the start point in the test corridor and video images of the walking area were recorded while the chicken walked from the start point to the end point of the corridor, a distance of 2.4 metres. This procedure was repeated with all 250 chickens.

4.2.2 Image analysis

The basic image analysis technique used was background subtraction for segmentation of the shape. This technique was used because the camera setup was fixed and hence the background remained constant over time. Segmentation was performed by subtracting a background image of the empty corridor from each recorded image of the corridor containing a chicken. A pixel for which the difference was above a certain threshold was defined as belonging to the shape of the animal (Leroy et al. 2005). After this process, the shape of the animal could be characterised using a set of measurable parameters, such as the centre of the shape mask or the area of the shape mask (Minagawaha and Ichikawa 2002; DeWet et al. 2003).

Table 4.1: Overview of chickens used in the experiments.

Overview of Chickens					
Gait Score	Number of Birds	Breed	Sex	Age in Days	Weight (kg)
GS0	50	$Ross - 308$	M	39	2.08
GS1	50	$Ross - 308$	M	39	2.19
GS2	50	$Ross - 308$	M	39	2.15
GS3	50	$Ross - 308$	M	39	2.30
GS4	50	$Ross - 308$	M	39	1.92

Furthermore, an image processing algorithm was used to extract a chicken from a sequence of video images, and the centre point, orientation, length and width of the animal in the image were defined by fitting an elliptical shape around the animal (Leroy et al. 2003, Leroy et al. 2005). Elliptical shapes are simple but widely applicable as an approximation of natural shapes (Birchfield 1998) and their shape can be altered by varying only five parameters: (xc, yc, α, a, b) respectively, where xc and yc are the centre coordinates, α is the rotation angle around the horizontal axis, and a and b are the lengths of the major and minor axis. This reduces the image processing time in such a way that it can be used on-line (Leroy et al. 2005). The general flowchart of the image analysis and classification procedure can be seen in Figure 4.2. For initialisation purposes, the centre point, position, orientation and sizes of the chicken mask obtained from background subtraction were calculated in the first image of each video sequence and fed into the program. The optimal value of the shape parameters (xc, yc, α, r1, r2) for each image was labelled as posture parameters and stored for further processing (Leroy et al. 2005). When a certain type of behaviour occurred in the camera image, this caused a distinctive pattern in a number of successive posture parameter values. The posture parameters for each image were computed and the past values within a certain time window were analysed, so that the window could hold the entire pattern (Leroy et al. 2005). A first order transfer function (TF) model was used to model the dynamic trajectories of the posture parameters within the time window (Young 1984). Fitting this function to the data within each time window resulted in a set of two dynamic parameters a, b for each posture parameter (Leroy et al. 2005). Table 4.2 summarises the dynamic variables that were extracted.

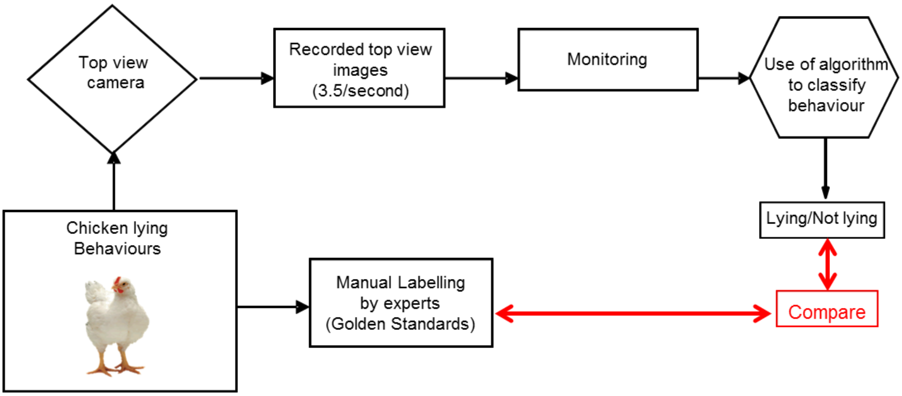

Figure 4.2: Flowchart of the image analysis and classification procedure

Table 4.2: Dynamic variables extracted from the video sequence of the chickens and their description.

Dynamic Variables		
Variable name	Description	Units
x-y coordinates	x y coordinates of animal centre in the pen as a function of time	*m*
Walking trajectory	Subsequent positions of the animal's mass centre in x and y coordinates	*m*
Orientation	Subsequent angles of the chicken with respect to the horizontal axis in the image as a function of time	*degrees*
Back area	Top view area of chicken	

4.2.3 Classification of lying behaviour

The classification procedure involved the variables: walking trajectory, orientation change, x - y coordinates and back surface area of the chicken. These variables were analysed by applying a sliding window approach. The chicken's behaviour was classified as lying (lying) if during the past window size (3.5 frames per second): 1) The slope of the cumulative distance walked was below a certain threshold; 2) The x-y coordinates of the geometric centre of the animal were stable, meaning that the fluctuations remained within a certain stability range expressed as a percentage; 3) The filtered back area variable of the animal (m^2) exceeded a certain threshold (Cangar et al. 2008). If these conditions were fulfilled the chicken's behaviour was classified as lying. The resulting output from this method consisted of the animal's position, orientation and body configuration as a function of time. Using these outputs, a distinction between lying and standing was made automatically. Latency to lie down (LTL) of broiler chickens was also calculated. Unlike previous studies, this study did not use any kind of disturbing factor such as water to measure LTL in broiler chickens. The experiments were conducted on a commercial farm. Manual labelling of lying down events and assessment of the duration of the latency to lie down were carried out by an expert during the experiments. Afterwards, the results from the proposed algorithm were compared with manual labelling results.

4.2.4 Statistical analysis

The statistical analysis was carried out on 50 video data sets per experiment with 10 data sets belonging to each of the gait score groups. In total, 250 data sets were used to investigate the differences in lying behaviour between the gait score groups. The Friedman test, which is a non-parametric test that compares the columns without the row effects, was used to analyse the effects of gait score on birds' lying behaviour. In the test sample, size and dependencies did not affect the test results. Following the Friedman Test, the Dunn test was applied to define the statistical differences between the gait scores. The Dunn post test compares the difference in the sum of ranks between two columns with the expected average difference (based on the number of groups and their size).The calculations were performed using the Statistics Toolbox of Matlab (The Math Works, Massachusetts, USA).

4.3 Results

4.3.1 Classification of lying

This automated monitoring tool made it possible to measure the body variables back area, centre point and body contour (Table 4.2). The walking trajectory of chickens, measured using this tool, during the experiments is shown in Figure 4.3.

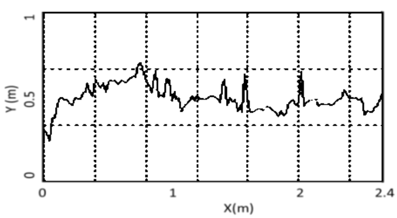

Figure 4.3: Walking trajectory of chicken 1 during the experiment.

The line in the figure shows the x-y coordinates of the centre point of the chicken in the walking corridor. The figure gives a good indication of the walking trajectory (in the x-y direction of the walking corridor) during the experiment. A change in orientation (rotation angle around the horizontal axis) was a clear indicator of animal activity. There were some occasions when the orientation of the bird changed although its centre point did not change; this signified a clear movement but no displacement (see Figure 4.4).The x-y coordinates and the speed of the centre point, together with the orientation of the main axis of the chicken, is plotted as a function of time in Figure 4.5. X-y coordinates indicated the specific position of the chicken in the corridor at a specific time. Little variation in the x-y coordinates indicated that movement of the chicken was limited. During those periods the chicken was either standing and not moving or lying down. Acceleration (m/s^2) was another representation of the chicken's movements.

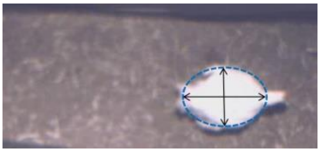

Figure 4.4: The ellipse and the centre point of broiler chickens.

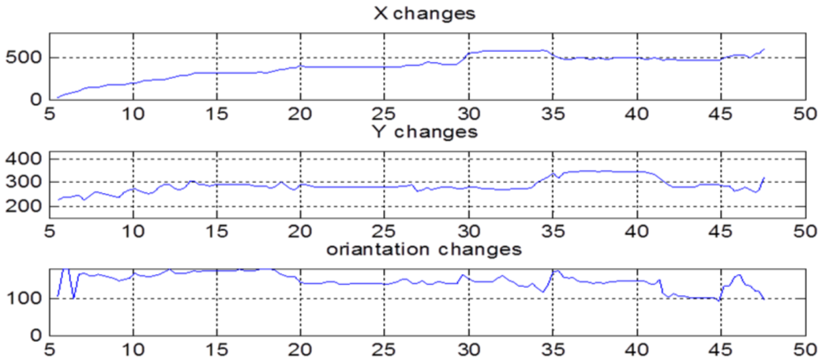

Figure 4.5: X position, Y position and the orientation changes (degrees) of chicken 1 during experiment.

Not surprisingly, the speed was approximately zero during lying periods. Variations in the x-y coordinates over time and a speed greater than zero signified that the chicken was moving. This movement could be an indication of walking or could be indicative of lateral movements while in the lying position. The percentage of correctly classified lying behaviour for 250 chickens can be seen in Table 4.3. The x-y position, back area and acceleration, in particular, demonstrated a strong correlation with manual labelling of the lying and standing behaviour.

When the slope for the cumulative distance was high, the animal was standing and moving. On the other hand, when the slope was close to zero, the chicken was lying or standing still. While lying, the back area was greater than while standing or walking. Compared with manual labelling, the image analysis method correctly classified lying behaviour in 250 chickens with an average accuracy of 83 percent.

Table 4.3: Correctly classified lying behaviour using image analysis.

Correct Classification						
Exp.	NoL (Alg.)	NoL(Man.Lab.)	TP	FP	FN	Accuracy
1	126	118	99	27	19	84
2	120	115	93	27	22	81
3	118	111	89	29	22	80
4	135	128	112	23	16	88
5	129	113	93	37	20	82
Avg	126	117	97	29	20	83

A linear regression test was performed to define the coefficient of determination between the number of lying events obtained by the proposed algorithm and the number of lying events obtained by manual labelling, which resulted in R^2 = 0.993. Afterwards, the relationship between the latency to lie down (LTL) obtained with the algorithm and LTL obtained by manual labelling was investigated and the coefficient of determination (R^2) was found to be 0.997.

4.3.2 Assessment of lying behaviour in relation to gait score

The results of the algorithm were statistically analysed for differences between the different gait score levels. As shown in Table 4.4, the number of lying events (NoL) in GS3 and GS4 (mean +/- standard deviation) was significantly ($P<0.001$) higher than in GS0, GS1 and GS2 (Figure 4.6).

Moreover, there are no significant differences between GS0, GS1 and GS2 in terms of the number of lying events (NoL). The LTL was also evaluated and the results are presented in Table 4.4. Lame chickens with GS3 and GS4 (mean +/-standard deviation) sit down significantly ($P<0.001$) earlier than those with GS0, GS1 and GS2 (Figure 4.7). The results show a high correlation (R^2 = 0.987 and $P < 0.001$) between NoL and LTL (Figure 4.8).

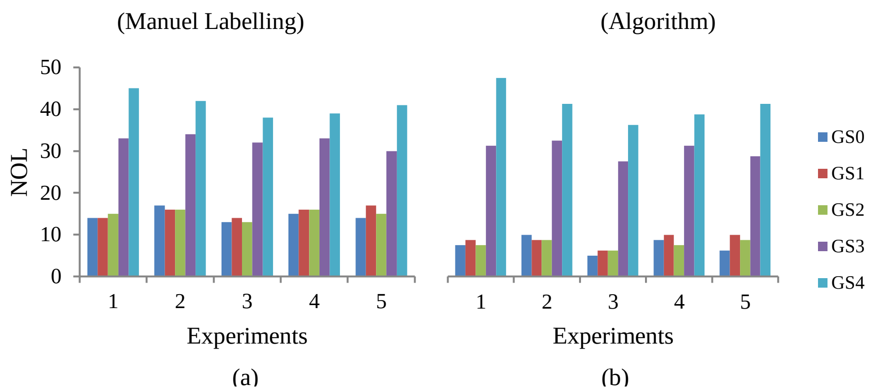

Figure 4.6: The number of lying events for broiler chickens (a) NoL obtained by algorithm, (b) NoL obtained by manual labelling.

Table 4.4: NoL and LTL of broiler chickens with different gait scores.

Gait Scores	NOL (Mean+Std)	LTL (s) (Mean+Std)
0	16±2[a]	28.69±11.30[a]
1	17±1[a]	25.27±09.43[a]
2	16±1[a]	23.56±07.86[a]
3	34±2[b]	11.15±05.46[b]
4	43±3[c]	03.33±01.75[c]

[a] a,b Means, within a column, with no superscript in common differ significantly (P < 0.05). X± standard deviation, n = 5.

The minimum and maximum LTL values recorded were 19.06-45.16 s for gait score 0, 15.08-37.14 s for gait score 1, 16.02-35.09 s for gait score 2, 5.16-18.11 s for gait score 3, and 1.66-6.24 s for gait score 4.

The relationship between lying and gait score is shown in the correlation between NoL, LTL and gait score (Figure 4.8). The analysis revealed a strong positive correlation (R^2=0.893) between NoL and gait score and a strong negative correlation (R^2 = -0.954, P < 0.001) between LTL and gait score.

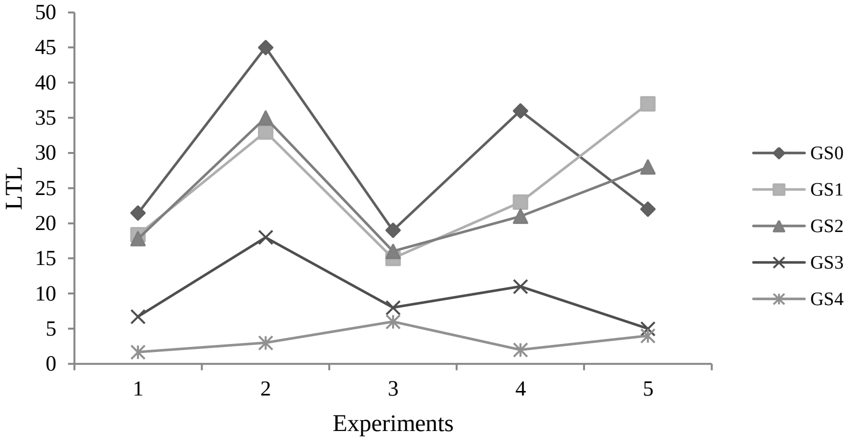

Figure 4.7: Latency to lie down in broiler chickens.

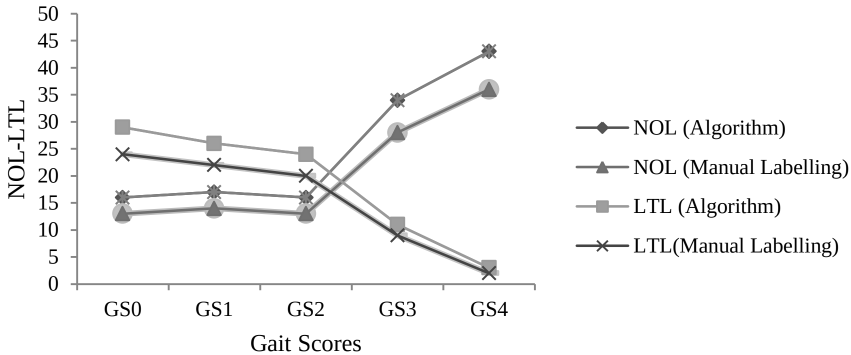

Figure 4.8: Correlation between gait scores, lying and LTL behaviours of broilers and comparison of algorithm output against manual labelling.

4.4 Discussions

A novel technique using computer vision was developed to automatically monitor the gait variables and coordinates from top view images of individual broilers. It provided broad information based on the centre point, body contour, walking trajectory and back area of broilers. The variables obtained were then used for classification of lying behaviours such as lying events and latency to lie down. These classified behaviours were then compared with manual labelling by experts. It was found that on average 83 percent of the lying behaviour of the 250 chickens during the experiments could be correctly classified. On the other hand, the results of this study also showed a clear correlation (R^2=0.0893) between gait scores and lying behaviour of broiler chickens; this was similar to the results of Weeks et al. (2000). As concluded in the study by Weeks et al. (2000), sound broilers averaged 76 percent of 23 hours lying and this increased significantly to 86 percent of 23 hours in lame birds. Based on the well-known latency to lie test, a lame chicken would spend a longer part of the day lying and it also tends to sit down much sooner than a sound chicken. The automatically extracted LTL was evaluated and the results showed a similarity with the results of Weeks et al. (2002); the lame birds (GS3 and GS4) sat down significantly ($P<0.001$) earlier (03.33+/-01.75 sec.) than the sound birds (Figure 4.7).

This study also indicates that lame chickens tend to have a lower latency to lie down than non-lame chickens. Berg and Sanotra found a clear negative correlation (R^2= -0.86, $P < 0.001$) between LTL and gait score (Berg and Sanotra 2003). Similarly, in this study, a strong negative correlation ($R^2 = -0.954$) was found between the LTL and gait score level of broiler chickens. Comparable results were also found by Dawkins et al. (2009), with gait scores highly negatively correlated with the percentage of time chickens spent walking. This study went beyond the previous studies to investigate the NoL in broiler chickens, and the analysis revealed a strong positive correlation ($R^2 = 0.893$) between NoL and the gait score levels of broiler chickens. Further, the results of the algorithm were statistically analysed for differences between the different gait score levels. The NoL in lame chickens (GS3 and GS4) was significantly ($P<0.001$) higher (34+/-2 and 43+/-3) than the NoL in sound chickens (GS0, GS1 and GS2). Although there were strong correlations between NoL, gait score and LTL, there were no significant differences between sound chickens (GS0, GS1 and GS2) in terms of NoL and LTL.

In this study, only the broiler breed Ross 308 was used in order to produce comparable data. The results and conclusions of this research apply to the behaviour of Ross 308 chickens, which is the most common breed in Europe. The lying behaviour may be different in other breeds or genetic lines. The classified behaviours were compared with manual labelling by experts. Strong correlations were found between the outcome of the algorithm and manual labelling, leading to the conclusion that the algorithm produces reliable results. However, correct classification of lying down averaged 83 percent, indicating that there is room for improvement. On some occasions the cumulative distance slowly increased even when the chicken was lying. This could be due to the amount of interference that was accumulated during position measurement or because of real movement of the bird’s centre point while standing. The same conclusions could be drawn when looking at changes in the back area of the bird. To enhance the accuracy of the system, a possible improvement might be to use a high-resolution camera recording with a higher frame rate. Although improvements are needed in order to achieve a better classification rate, the results suggest that this automatic image analysis system has the potential to serve as a tool for monitoring and assessing the lying behaviour of broiler chickens in relation to lameness incidences.

4.5 Conclusions

This main focus of this research was to investigate the relationship between automatically classified lying behaviour and the gait scores of individual broiler chickens in order to assess the lameness of broilers. 83 percent of lying behaviour was correctly classified by this automatic monitoring system for a total of 250 broiler chickens. The system has potential but needs further optimisation to improve classification and also needs to be validated in different field conditions, on different types of chickens and on a larger sample size of broilers.

If validation is successful, the monitoring technique developed is a promising tool for analysing lying behaviour and indicating lameness in broiler chickens. As also concluded by Rushen et al. (2012), for more accurate identification of the effects of gait score on broiler behaviour, this automatically obtained lying information can be combined with other automatic behaviour analysis systems, such as measuring the activity levels of chickens to detect the degree of lameness (Aydin et al. 2010) and/or detecting the optical flow patterns in broiler chicken flocks as suggested by Dawkins (2009 and 2012).

The advantage of this type of automated system is that measurements can be taken continuously throughout the life-span of a flock, and that measurement is fully automated, completely non-invasive and non-intrusive and does not involve the biosecurity risk of people visiting different farms to perform gait scoring (Dawkins et al. 2009). The additional advantage of taking measurements continuously throughout the life of a flock increases the likelihood that such tools can also be used for welfare assessment purposes. For example, an early detection system using these combined automated monitoring systems can be set up in a commercial broiler house to detect lameness before the GS4 and GS5 levels are reached by continuously tracking the different behaviours of broiler chickens.

4.6 Link with other chapters

Previous chapters describe studies in which broiler responses were continuously monitored and the lameness of birds assessed by measuring different types of variable such as activity levels, exploration and locomotion behaviours and body posture parameters using image processing technologies.

However, a continuous monitoring tool based on an image analysis technique is not sufficient on its own to assess broiler behaviour, health and welfare. The results presented in previous chapters show that all seriously lame birds (GS4, GS5) have a significantly lower weight ($p > 0.05$). This leads us to Chapter 5 and the evaluation of the next hypothesis, which states that automatic recording of pecking sounds from broilers allows measurement of feed uptake and assessment of the feeding behaviour of chickens in real time. Therefore, having investigated lameness in broiler chickens using different monitoring techniques based on vision technology, feeding behaviour is now examined using real-time sound analysis. In chapter 5, sound-based technology is used instead of vision to obtain information about the pecking and feeding behaviour of broilers.

Chapter 5

A novel method to automatically measure the feed intake of broiler chickens by sound-based technology

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5.1 Introduction

The need for livestock monitoring and the integration of animal responses in livestock farming has been reviewed by Frost et al. (1997) and Aerts et al. (2003). Recent years have seen increasing interest in the analysis of farm animal vocalisation and a variety of attempts to decode the meaning have been made. For example, Enting et al. (2000) described a knowledge-integrated computer system to support health management in pig farms. Other approaches have examined the relationship between vocalisation (VanHirtum and Berckmans 2004), drinking behaviour or temperature (Geers et al. 1997) and pig health (Silva et al. 2008; Ferrari et al. 2008; Guarino et al. 2008; Exadaktylos et al. 2008).

Alongside pig vocalisations, there has also been extensive research into poultry behaviour and welfare related to sound vocalisation (Evans and Evans 1999). The question of how poultry behaviour and/or well-being may be influenced by management or environmental stimuli has been studied. Researchers are trying to investigate which responses should be measured and whether bird responses are correlated to well-being. One means of assessing bird response to stimuli involves careful analysis of individual or group characteristics over time. Monitoring individual behaviour during research trials is typically performed using a video imaging system. For poultry, behavioural activities are categorised into events such as eating, drinking, preening, resting, and stereotyped activities directed at different targets. This assessment methodology is time-consuming, hence costly, tedious and prone to errors, even with modern commercially available research systems that compile the statistics semi-autonomously.

Therefore, there is an increasing need for methods for further automatic collection of event-based behavioural responses (Gates and Xin 2001; Persyn et al. 2004; Xin et al. 1993). For this purpose, computer and modern electronic technologies have been used to monitor bird feed intake, body weight and feed conversion ratio (Hulsey and Martin 1991; Xin et al. 1993; Yo et al. 1997; Savory and Mann 1999; Puma et al. 2001). For example, Gates and Xin (2008) developed algorithms for determining individual bird feeding statistics and stereotyped pecking behaviour from time-series recordings of feed weight and compared them to video observations. In another study, focussing on turkey breeding, Xuyong et al. (2011) developed a structured query language (SQL) database management system to record and manage the dynamic feed intake and body weight gain data of individual birds.

However, up to now, the same methodology has been applied by defining poultry feed intake based on weighing scale data. For example, Kutlu and Forbes (2000) investigated the feeding pattern of broiler chickens by means of continuous recording of feeder weight. At the same time, sound recording started to be used for calculation of the feed intake of various animal species (Laca and Vries 2000). For instance, Laca and Wallis De Vries studied acoustic measurements of feed intake and grazing behaviour of cattle by attaching three microphones to each animal (Laca and Vries 2000).

In this research, a novel method is investigated by using a sound detection system to calculate the feed uptake and feed intake of broiler chickens. In contrast to previous studies, this is the first time that a sound detection system has been used in the feeder instead of attaching a device to each animal. A major advantage of this sound detection system is that measurements can be recorded continuously throughout the life span of a flock, in a fully automated, completely non-invasive and non-intrusive way. The objectives of this research are: (1) to test, develop and validate an algorithm for detection of individual bird pecking sounds and (2) to obtain a novel method for estimating absolute amount of feed uptake, feed wastage and feed intake in broiler chickens.

5.2 Materials and methods

5.2.1 Experimental setup

The recordings were carried out with 12 broiler chickens on three consecutive days. Three experiments were conducted with each broiler, giving a total of 36 experiments. Each individual chicken was housed in a different cage without access to feed and water for four hours before the experiment in order to stimulate pecking at the start of the experiment. Each experiment lasted for 15 minutes. During the experiment an individual bird was placed in a separate cage (50x50x50 cm).

All sounds, such as pecking, vocalisation and environmental sounds, were continuously recorded. At the same time, video images were captured and feed uptake by the chicken was continuously recorded (sampling frequency of 10 Hz) by means of a weighing system which was connected to the PC via RS-232 cable. After all the data had been recorded, the sound data were analysed using a pecking detection algorithm in MATLAB (Mathworks). For validation of the proposed algorithm, pecks by the chicken in the image data were manually labelled using the labelling tool developed by Leroy et al. (2005). A second validation based on the measured weighing data was also used. For the sound recording, an electret microphone (Monacor ECM 3005) was attached to the underside of the feeding pan (Figure 5.1). The microphone had a frequency response of 30-20,000 Hz and was connected to the PC via a preamplifier (Monacor SPR-6). All recordings were sampled at a 44.1 kHz with a 16 bit resolution. The video recordings were taken using a USB webcam (Logitech Webcam Pro

9000) with 3.7 mm Carl Zeiss lens mounted next to the cage at a distance of 50 cm with its lens pointing towards the cage in order to give a side view of the feeder (Figure 5.1).

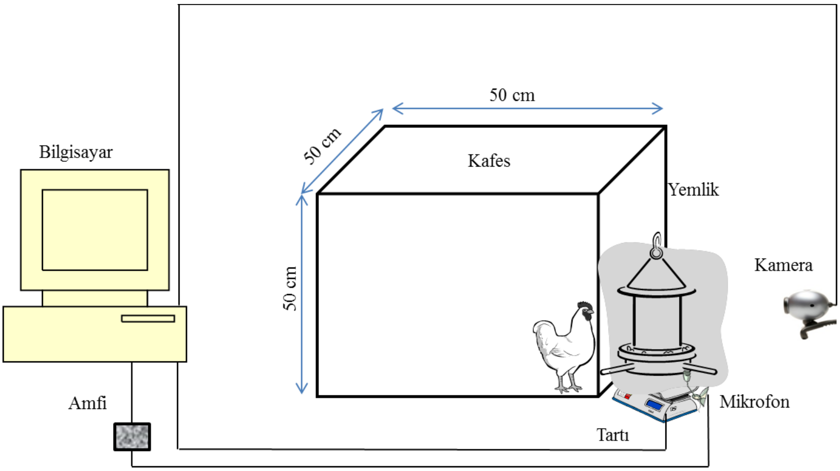

Figure 5.1: Laboratory setup for sound recordings of an individual chicken.

Images were captured with a resolution of 640 horizontal by 480 vertical pixels at a sample rate of 15 frames per second. During the video recordings, illumination was maintained at 10 lux. The feeding pan was placed on a precision balance (KERN PCB-250-3, with weighing range 250 g and accuracy 0.001 g).

5.2.2 Birds and housing

The experiments were carried out with twelve 28-day old, male, Ross 308 broilers. The birds were vaccinated, following standard procedures, both at the hatchery and in the broiler house on day 23. For the first nine days, a pre-starter diet with 23 percent protein and 2890 kcal AMEn/kg (apparent metabolisable energy) was given. From day 10 until day 13 a starter diet with 22 percent protein and 2794 kcal AMEn/kg, and from day 14 to day 32 a grower diet with 20 percent protein and 2899 kcal AMEn/kg was provided. The birds were transported to the laboratory in two hours from a local farm (Provincial Center for Applied Poultry Research, Geel, Belgium). Birds were kept in floor pens measuring 0.5x0.5x0.5 m with wood shavings. Feed and water were freely available to birds during the experiments. The birds were allowed two days of adaptation in order to recover from the stress of transport and acclimatise to their new environment.

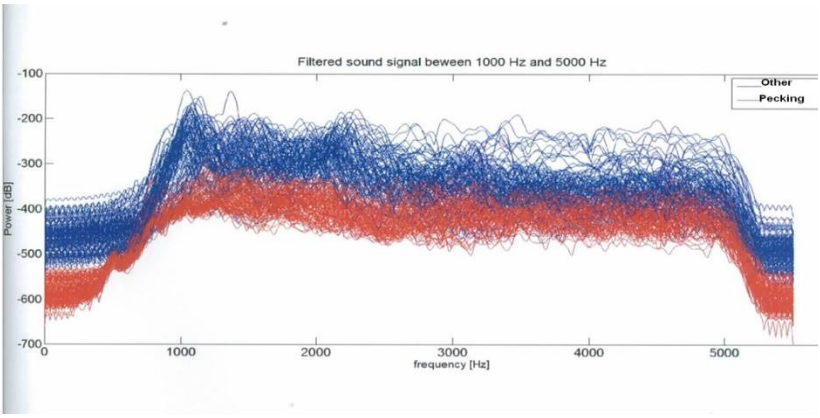

Figure 5.2: Filtered sound signal (pecking and other) between 1 kHz and 5 kHz.

5.2.3 Definition of frequency ranges

Before sound extraction was applied, the recorded data were pre-processed in order to define the best frequency differences between pecking and other sounds. Afterwards, the individual sounds (pecking and other sounds) were manually extracted from the continuous recordings and stored as individual sounds. The resulting data set of 100 individual pecking sounds and 100 other sounds was used to define the best frequency differences between pecking and other sounds.

5.2.4 Filtering

To eliminate low-frequency noise produced mainly by the ventilation system in the laboratory, the signal was initially band pass-filtered (6th order Butterworth filter) with cut-off frequencies of 1 kHz and 5 kHz (Figure 5.2). The pecking sound signals which needed to be recognised are not affected by this filter as they have considerable low frequency components and the frequency range between 1 kHz and 5 kHz holds enough information for the purposes of this study. Figure 5.2 shows the filtered sound signal between 1 kHz and 5 kHz. After band pass filtering, the signal was down-sampled from 44.1 to 11.025 kHz to reduce processing time. The flowchart for the proposed signal processing procedure is shown in Figure 5.3.

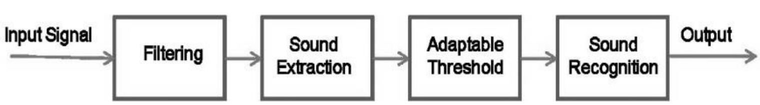

Figure 5.3: The flowchart used for the proposed algorithm.

5.2.5 Sound extraction

The algorithm is composed of two major parts: first, the individual sounds are extracted from a continuous recording, and afterwards each sound is classified as pecking or other sound. Each part of the algorithm is presented in detail in the following sections. Extraction of individual sounds from a continuous recording is based on the envelope of the energy of the signal and is automatically selected by applying a specific threshold (Exadaktylos et al. 2008). The mean value of the envelope over the complete recording is used for this application assuming that it is adequate for extracting most of the signals that are of interest. To automatically calculate the envelope of the continuously recorded signal, the Hilbert transform of a discrete time signal s[k] is defined as providing a 90 phase shift to the original signal and is used according to the following algorithm procedure: 1. calculation of the energy of the signal, calculation of the Hilbert transform of the energy; 2. calculation of the square root of the sum of the energy and its Hilbert transform; and 3. calculation of the moving average of the result to give a smoothed estimate of the envelope of the initial signal. The result of this procedure is presented in Figure 5.4, where a continuous sound signal is presented and the extracted pecking sounds are also shown.

5.2.6 Sound classification

The sum of the power spectral density vector was calculated for a frequency range between 1 and 5 kHz in order to identify whether the sound is a peck or not. This frequency range was identified because the peck and the other sound signals have very different frequency content. Based on this, the threshold value can be chosen in the ranges that differentiate the other sound from the pecking sound signal. In this research, an adaptable threshold was chosen instead of a fixed threshold because the frequency contents of pecking and other sound signals are not stable and not easily distinguishable.

Every individual sound signal was automatically calculated by the algorithm to give a new and correct threshold value. Each threshold was defined as 0.8 per cent of the maximum signal. However, it should be noted that the noise level and the acoustics at a commercial broiler farm are different from the laboratory environment, which can affect the resulting signal. Therefore this should be taken into account when choosing the threshold. After threshold definition, the algorithm classified the sound based on a sudden increase of amplitude in both spectrogram(s) and wave forms together with a subsequent decrease. Figure 5.5 shows a spectrogram of a continuous sound consisting of several individual pecks. If the sum of the density is below the threshold in the frequency band, the signal is characterised as a peck.

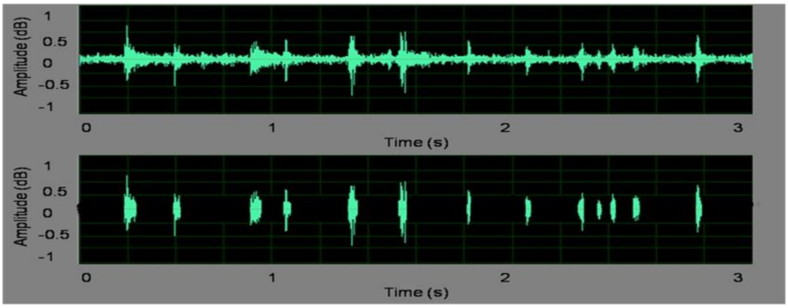

Figure 5.4: Continuous recording of sounds (top) and individual pecking sounds (bottom) as extracted by the algorithm.

5.2.7 Feed intake calculation

Feed uptake was automatically calculated using a sound algorithm which detected the pecking sounds from broiler chickens. At the same time, it was continuously recorded by a weighing system while wasted feed was collected and weighed manually after each experiment (see Table 5.1). The feed intake per experiment lasting 15 minutes (FIPE) is defined as: FIPE=FUPE-FWPE (1)

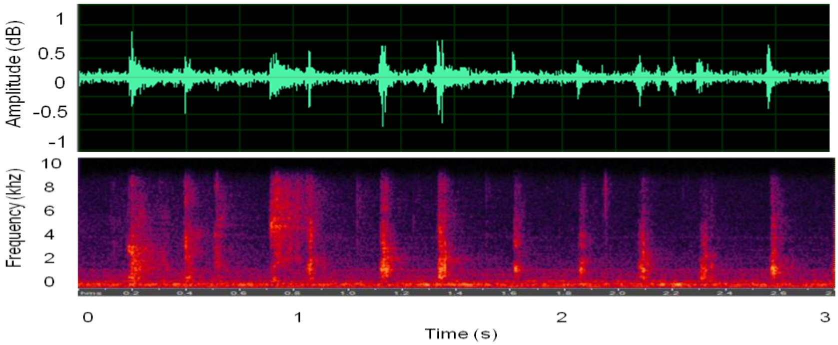

Figure 5.5: Spectrogram of a continuous sound (consisting of 13 pecking hits) represented in the time domain (top) and in the frequency domain (bottom).

The feed intake per experiment (FIPE) is the quantity (g) of feed ingested by chickens during the experiment. This value was calculated by subtracting the feed wastage per experiment (FWPE) (quantity (g) of feed spilled onto the ground) from the feed uptake per experiment (FUPE) (quantity (g) of feed removed from the feeder by the chicken during the experiment). The feed intake per peck (FIPP) is the quantity (g) of feed ingested by chickens with each peck. This value was calculated as the ratio between the total feed intake per experiment (FIPE) and the total number of pecks per experiment (NPPE). FIPP=FIPE/NPPE (2)

5.3 Results

The first main goal of this study was to develop an accurate algorithm to detect broiler pecking sounds. All sounds were processed and classified as either "pecking" or "other sound" using the proposed algorithm. Table 5.1 shows the total number of pecking sounds identified automatically by the algorithm and the total number of pecking sounds labelled visually by using the video reference. False positives were obtained when a sound of another nature were falsely identified as pecking. As can be seen in Table 5.1, 93 percent of the pecking sounds were correctly identified, while the false positive results were low, averaging 7 percent (range 4-11).

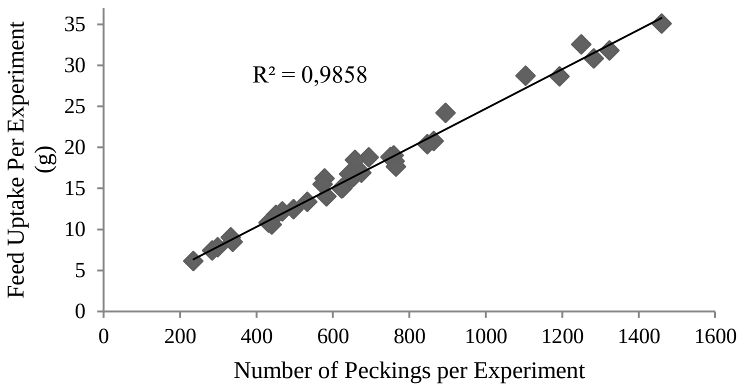

Figure 5.6: The relationship between feed uptake and number of pecks by chickens per experiment.

The results presented are based on sounds recorded in laboratory conditions using 12 animals in total. The second main goal of this research was to investigate the relationship between pecking sounds and feed intake by chickens. All sound data were analysed by the algorithm in order to detect the total number of pecks in each experiment. Additionally, feed uptake (FUPE) was measured by the weighing system and the data were linked to the results from the sound algorithm (see Table 5.2). The lowest feed intake per peck was 0.023 g in the second experiment using the eleventh chicken (see Table 5.2). The highest feed intake per peck was 0.028 g in the third experiment using the fourth chicken (see Table 5.2). The average feed intake per peck was 0.025 g.

Before estimating the absolute amount of feed intake by chickens from the pecking sounds algorithm, the relationship between the number of pecks and feed uptake by chickens was investigated. A linear relationship between the variables was identified (see Figure 5.6). All sound data were analysed with an interval of one minute and compared to feed uptake per minute in order to ascertain the strength of the linear relationship between the variables (see Figure 5.7). Afterwards, a linear regression test was performed and the coefficient of determination (R^2) was found to be 0.995 (see Figure 5.7). In addition to the high correlation, 90 percent of feed intake was correctly monitored through sound analysis.

Table 5.1: Accuracy results for the proposed algorithm.

Data Set	NoP (Alg.)	NoP (Labelling)	Accuracy"%"	True Positive	False Positive
1	113	105	93	105	8
2	99	95	96	95	4
3	109	106	98	106	3
4	98	91	93	91	7
5	97	88	91	88	9
6	105	95	90	95	10
7	105	99	95	99	6
8	97	92	95	92	5
9	107	98	92	98	9
10	105	97	92	97	8
11	104	94	91	94	10
12	108	100	93	100	8
13	99	91	92	91	8
14	96	90	93	90	6
15	112	108	97	108	4
16	109	98	90	98	11
17	100	91	91	91	9
18	103	97	94	97	6
19	105	95	90	95	10
20	108	99	91	99	9
21	97	89	92	89	8
22	96	89	93	89	7
23	96	88	91	88	8
24	99	95	96	95	4
36	95	88	92	88	7
Tot/Avg.	3707	3447	93	3447	260

Table 5.2: Number of pecking, feed uptake feed loss and feed intake of chickens.

Chic	Exp.	NPPE	FUPE (g)	FWPE (g)	FIPE (g)	FIPP (g)	FIPP (Mean± std)	FWPE (%)
.	1	1193	28.63	0.325	28.31	0.024		1.14
1	2	759	18.98	0.198	18.78	0.025	0.025±	1.04
	3	895	24.17	0.222	23.94	0.027	0.0015^{a}	0.92
	1	1250	32.50	0.236	32.26	0.026		0.73
2	2	1283	30.79	0.365	30.43	0.024	0.025±	1.19
	3	1460	35.04	0.348	34.69	0.024	0.0012^{a}	0.99
	1	651	16.28	0.168	16.11	0.025		1.03
3	2	468	12.17	0.111	12.06	0.026	0.025±	0.91
	3	533	13.33	0.124	13.20	0.025	0.0006^{a}	0.93
	1	625	15.00	0.145	14.86	0.024		0.97
4	2	284	7.38	0.078	7.31	0.026	0.026±	1.06
	3	578	16.18	0.156	16.03	0.028	0.0020^{a}	0.96
	1	333	8.99	0.096	8.90	0.027		1.07
5	2	235	6.11	0.059	6.05	0.026	0.026±	0.97
	3	299	7.77	0.078	7.70	0.026	0.0006^{a}	1.00
	1	694	18.74	0.145	18.59	0.027		0.77
6	2	658	18.42	0.158	18.27	0.028	0.026±	0.86
	3	864	20.74	0.195	20.54	0.024	0.0021^{a}	0.94
	1	440	10.56	0.095	10.47	0.024		0.90
7	2	675	16.88	0.162	16.71	0.025	0.025±	0.96
	3	451	11.73	0.111	11.62	0.026	0.0010^{a}	0.95
	1	847	20.33	0.187	20.14	0.024		0.92
8	2	623	14.95	0.123	14.83	0.024	0.024±	0.82
	3	338	8.45	0.088	8.36	0.025	0.0006^{a}	1.04
	1	1324	31.78	0.298	31.48	0.024		0.94
9	2	762	18.29	0.151	18.14	0.024	0.024±	0.83
	3	761	18.26	0.145	18.12	0.024	0.0000^{a}	0.79
	1	643	16.72	0.201	16.52	0.026		1.20
10	2	751	18.78	0.222	18.55	0.025	0.025±	1.18
	3	497	12.43	0.129	12.30	0.025	0.0006^{a}	1.04
	1	1104	28.70	0.333	28.37	0.026		1.16
11	2	765	17.60	0.181	17.41	0.023	0.025±	1.03
	3	432	10.80	0.123	10.68	0.025	0.0015^{a}	1.14
	1	583	13.99	0.145	13.85	0.024		1.04
12	2	654	16.35	0.165	16.19	0.025	0.025±	1.01
	3	573	15.47	0.155	15.32	0.027	0.0015^{a}	1.00
Total-Average		25285	633.26	6.22	627.04	0.025	0.025± 0.0011^{a}	0.98

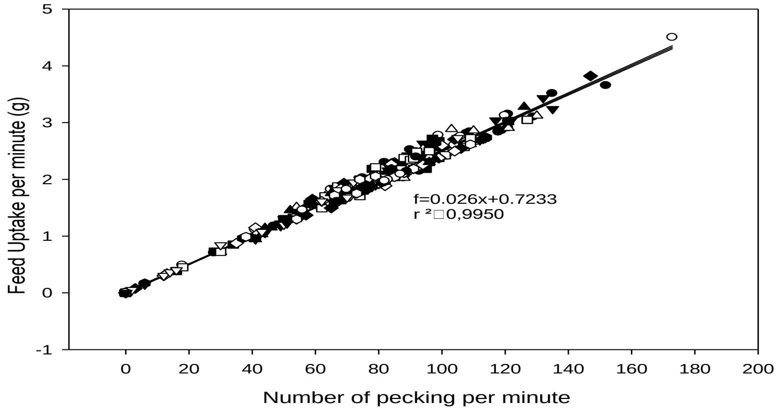

Figure 5.7: The correlation between feed uptake per minute and number of pecks per minute.

Furthermore, the relationship between the feed intake per experiment and the number of pecks per experiment was investigated and the coefficient of determination (R^2) was found to be 0.985 (see Figure 5.8).

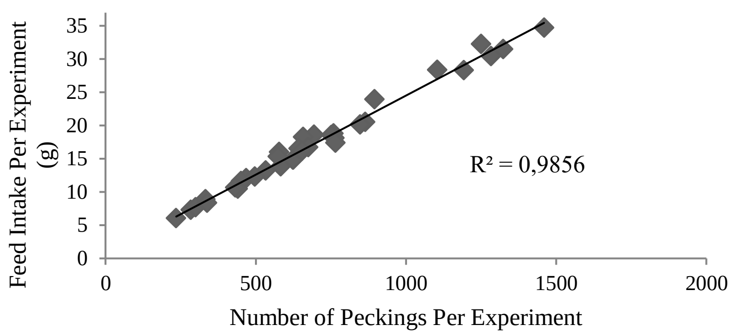

Figure 5.8: The relationship between feed intake per experiment and number of pecks per experiment.

As can be seen in Figure 5.9, the number of pecks was highly correlated with the feed intake of broiler chickens.

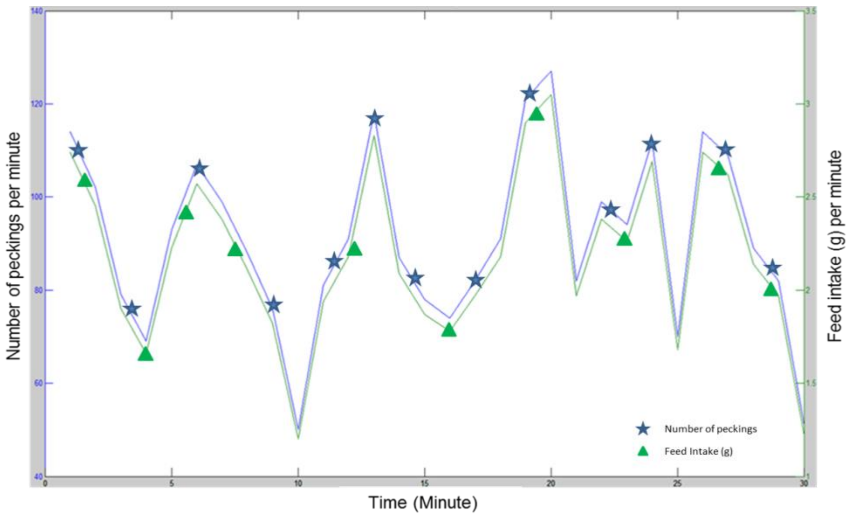

Figure 5.9: An example of the relationship between number of pecks and feed uptake by chickens.

5.4 Discussions

A novel technique was developed using sound recording to automatically detect pecks by broiler chickens. The tool allowed the pecking sounds from broiler chickens to be recorded by attaching the microphone to the feeder. The data obtained were automatically analysed and results show that 93 percent of the pecking sounds were correctly identified, while the false positive results were low, averaging 7 percent (range 4-11). In addition to pecking sound identification, the correlation between feed uptake, feed intake and number of pecks was calculated and a linear correlation between these three variables was identified. As the correlation between the number of pecks and feed intake by chickens resulted in $R^2 = 0.985$, the results suggest that this pecking sound detection system has the potential to be used as a tool to monitor the feed intake of chickens.

The advantage of this system is that measurements can be made continuously throughout the life-span of a flock, in a fully automated, completely non-invasive and non-intrusive way. However, it will be necessary to overcome a number of technical challenges in order to develop the proposed algorithm so that it will work under field conditions. The most important of these challenges is that each feeding pan in the farm might be easily modified by adding a very cheap microphone to rapidly and correctly calculate the feed intake of chickens. The real-time nature of the proposed algorithm makes it attractive as a means of measuring the absolute amount of feed intake by chickens at commercial broiler farms. It will be particularly useful in broiler houses where reliable measurement of feed intake is important in order to achieve the desired feed conversion rate, calculate the food wastage in each pen, define the eating period and define the dynamic feeding behaviour of chickens. Some methods of defining the feed intake of chickens have previously been presented in the literature. Two algorithms for determining individual bird feeding statistics and stereotyped pecking behaviour from time-series recordings of feed weight were developed by Gates and Xin (2008). Their research evaluated the effects of algorithm tuning parameters, including thresholds for changes in weight and sequential number of stabilised readings, arithmetic moving average for meal tare values, and the sampling frequency of feed weight recordings. They conclude that lower sampling frequencies are acceptable for determining hourly (or greater) feed consumption.

The results presented here are not directly comparable to those of Gates and Xin (2008) since their application refers to feed weight recordings, which is different from the current sound-based methodology. In any case, the applicability of the approach presented should be tested under farm conditions in order to obtain a more accurate evaluation. It should also be stressed that although the algorithm was tested on individual animals under laboratory conditions, the results showed that the algorithm is potentially of great value for objective studies of the feeding behaviour of chickens in future research.

5.5 Conclusions

This paper proposed a novel algorithm for detecting broiler pecking sounds. The results showed that the majority of sounds were identified correctly as pecking, with 93 percent accuracy. Furthermore, the relationship between feed intake and pecking sounds by broiler chickens was investigated and the results revealed that there was a very strong relationship between these two variables (R^2=0.985). Because of the high correlation, 90 percent of feed intake events were correctly monitored by means of sound analysis.

However, applying the method under field conditions will probably introduce problems which may affect the accuracy of the algorithm. For example, competition between the birds to reach the food and sounds from the ventilation system or feed dispenser will introduce a variety of sounds besides pecking. This will affect the frequency contents evaluated by the algorithm. However, these problems can be solved by studying and estimating the expected noise sequence and subsequent fine-tuning of the algorithm. Furthermore, animal age and various pathological conditions are believed to affect the frequency content of pecking signals and require further investigation. However, it is clear that sound monitoring could be used to define the feed intake of broilers. Apart from sound-based monitoring of broiler chickens housed in groups for breeding purposes, the real-time dynamic feed intake data provide an important basis for research into broiler feeding behaviour and welfare. Thus, further research should be aimed at defining dynamic feed intake, eating period, food wastage and feeding behaviour of broilers by sound analysis under different commercial farm conditions.

5.6. Link with other chapters

In this chapter, pecking sounds from individual chickens were recorded by attaching a microphone to the feeder, calculating the feed intake in real time and identifying the feeding behaviours of broilers.

In contrast to pecking sound detection for an individual bird as described in this chapter, Chapter 6 moves from an easy process to a slightly more complex situation to detect pecking sounds for a group of chickens while multiple birds were eating at the same time.

Chapter 6

A real-time monitoring tool to automatically measure the feed intakes of multiple broiler chickens by sound analysis

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6.1 Introduction

Researchers are trying to investigate which responses should be measured and whether bird responses are correlated to well-being. One means of assessing bird response to stimuli involves careful analysis of characteristics of individuals or groups over time. Monitoring individual behaviour during research trials is typically performed with some type of video imaging system. For poultry, behavioural activities are categorised into events such as eating, drinking, preening, resting, and stereotyped activities directed at different targets. This assessment methodology is time-consuming, hence costly, tedious and prone to errors, even with modern commercially available research systems which compile the statistics semi-autonomously.

Therefore, there is an increasing need for systems which can further automate collection of event-based behavioural responses (Gates and Xin 2001; Persyn et al. 2004; Xin et al. 1993). To this end, computer and modern electronic technologies have been used to monitor bird feed intake, body weight and feed conversion ratio (Hulsey and Martin 1991; Xin et al. 1993; Yo et al. 1997; Savory and Mann 1999; Puma et al. 2001). For example, Gates and Xin (2008) developed algorithms for determining individual bird feeding statistics and stereotyped pecking behaviour from time-series recordings of feed weight and compared them to video observations. In another study, Xuyong developed a structured query language database management system to record and manage the dynamic feed intake and body weight gain data of individual birds. The system developed also offers a powerful research tool for studying poultry feeding behaviour under group housing conditions (Xuyong et al. 2011).

However, until now, the same methodology has been applied as the feed intake of poultry has been defined on the basis of weighing scale data in the literature. Unlike previous studies in the literature to date, this work represents the first attempt to accurately measure the feed intake of broiler chickens at group level in a different, non-invasive way. This study differs from previous research as an advanced monitoring system was developed to automatically measure the feed intake of chickens at group level by real-time pecking sound analysis.

The objectives of this research were: (1) to develop the pecking sound detection capabilities of the existing algorithm while all the birds were eating at the same time, and (2) to provide a continuous monitoring system for further research and commercial use which can measure the feed intake of broiler chickens non-invasively at group level in farm conditions.

6.2 Materials and methods

6.2.1 Experimental setup

The pecking sounds from broiler chickens were recorded over 24 hours. In total, 24 experiments were conducted with 10 broilers at group level and each experiment lasted for 60 minutes.

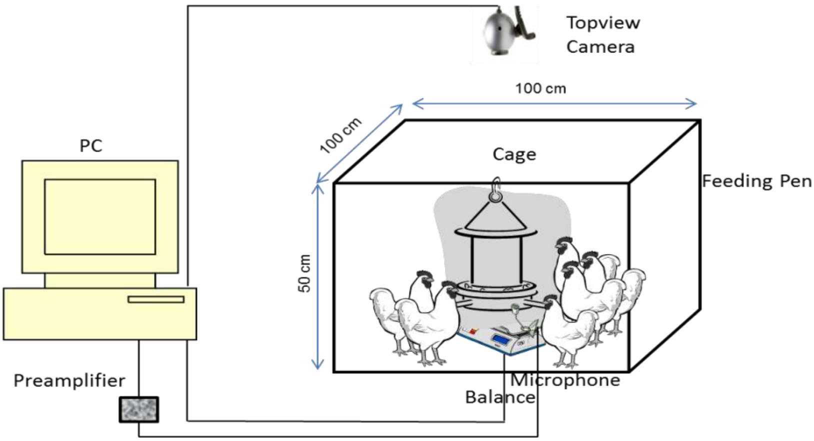

Figure 6.1: General setup with experimental materials (a), an example of a recorded top view image (b).

All chickens were housed in a different cage for four hours before the first experiment without access to feed and water so that they were hungry before the experiment. In contrast to our previous research, in this study all the birds were placed in one cage (100x100x100 cm) with a density of 10 birds per feeder and the pecking sounds were recorded while the all birds were eating. One commercial feeder was used in the experiment and an electret microphone (Monacor ECM 3005) was attached to the bottom of this feeder (Figure 6.1). The microphone had a frequency response of 30-20,000 Hz and was connected to PC via a preamplifier (Monacor SPR-6). All recordings were sampled at 44.1 kHz with 16 bit resolution. All sounds such as pecking, singing and environmental sounds were continuously recorded. At the same time, video images were captured with a top view camera. The video recordings were taken using a USB webcam (Logitech Webcam Pro 9000) with 3.7 mm Carl Zeiss lens mounted above the cage at a distance of 200 cm with its lens pointing towards the cage to give a top view of the feeder (Figure 6.1). Images were captured with a resolution of 640 horizontal by 480 vertical pixels at a sample rate of 15 frames per second. During the video recordings, illumination was maintained at 90 lux. As a reference measurement, the feed uptake of chickens was continuously recorded (sampling frequency of 10 Hz) by a weighing system, which was connected to the PC via RS-232 cable. The feeder was placed on a precision balance (KERN PCB-8000, with weighing range 8000 g and accuracy 0.01 g). The sound data were analysed by a pecking detection algorithm in MATLAB (Mathworks) and the feed intake of broilers was calculated based on pecking sound information. The weighing data were used to validate the proposed algorithm. The pecking sound results of the algorithm were compared to reference feed intake values through weighing system measurements.

6.2.2 Birds and housing

The experiments were performed with 10 male, 39-day old, Ross 308 broilers. The birds were vaccinated, following standard procedures, both at the hatchery and in the broiler house on day 23. For the first nine days, a pre-starter diet with 23 percent protein and 2890 kcal AMEn/kg (apparent metabolisable energy) was given. From day 10 until day 13 a starter diet with 22 percent protein and 2794 kcal AMEn/kg, and from day 14 to day 32 a grower diet with 20 percent protein and 2899 kcal AMEn/kg was provided. The birds were transported to the laboratory in two hours from a local farm (Provincial Center for Applied Poultry Research, Geel, Belgium). Birds were kept on the floor in pens 1x1x1 m on wood shavings. Feed and water were freely available to all birds during the experiments. The birds were allowed a two-day adaptation period in order to recover from the stress of transport and acclimatise to their new environment.

6.2.3 Definition of frequency ranges

Before sound extraction was applied, the recorded data were pre-processed in order to define the best frequency differences between pecking and other sounds. Afterwards, the individual sounds (pecking and other sounds) were manually extracted from the continuous recordings and stored as individual sounds. The resulting data set of 100 individual pecking sounds and 100 other sounds was used to define the best frequency differences between pecking and other sounds.

6.2.4 Filtering

To eliminate low-frequency noise produced mainly by the ventilation system in the laboratory, the signal was initially band pass-filtered (6th order Butterworth filter) with cut-off frequencies of 4 kHz and 5 kHz (Figure 6.2).

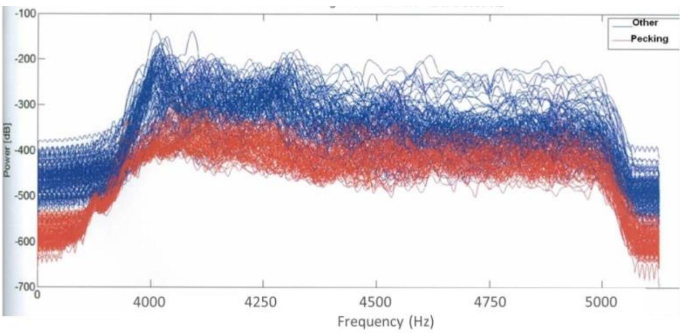

Figure 6.2: Filtered sound signal between 4 kHz and 5 kHz.

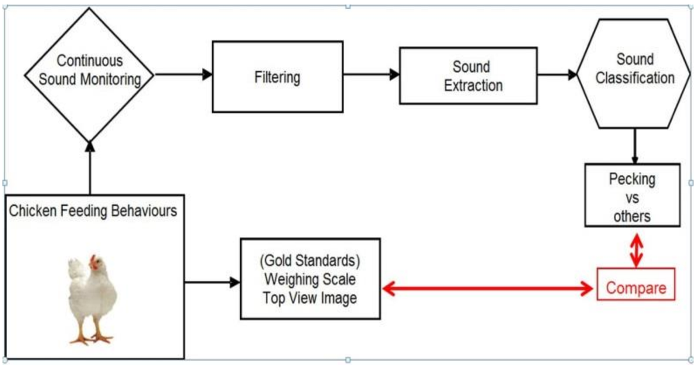

Figure 6.3: The flowchart for the proposed signal processing.

The pecking sound signals which needed to be recognised are not affected by this filter as they have considerable low frequency components and the frequency range between 4 kHz and 5 kHz holds enough information for the purposes of this study. Figure 6.2 shows the filtered sound signal between 4 kHz and 5 kHz. After band pass filtering, the signal was down sampled from 44.1 to 11.025 kHz to reduce processing time. The flowchart for the proposed signal processing procedure is shown in Figure 6.2

6.2.5 Sound extraction

The algorithm is composed of two major parts: first, the individual sounds are extracted from a continuous recording, and afterwards each sound is classified as pecking or other sound. Each part of the algorithm is presented in detail in the following sections. Extraction of individual sounds from a continuous recording is based on the envelope of the energy of the signal and is automatically selected by applying a specific threshold (Exadaktylos et al. 2008). The mean value of the envelope over the complete recording is used for this application assuming that it is adequate for extracting most of the signals that are of interest. To automatically calculate the envelope of the continuously recorded signal, the Hilbert transform of a discrete time signal s[k] is defined as providing a 90 phase shift to the original signal and is used according to the following algorithm procedure: 1. calculation of the energy of the signal, calculation of the Hilbert transform of the energy, 2. calculation of the square root of the sum of the energy and its Hilbert transform, and 3. calculation of the moving average of the result to give a smoothed estimate of the envelope of the initial signal. The result of this procedure is presented in Figure 6.4, where a continuous sound signal is presented and the extracted pecking sounds are also shown.

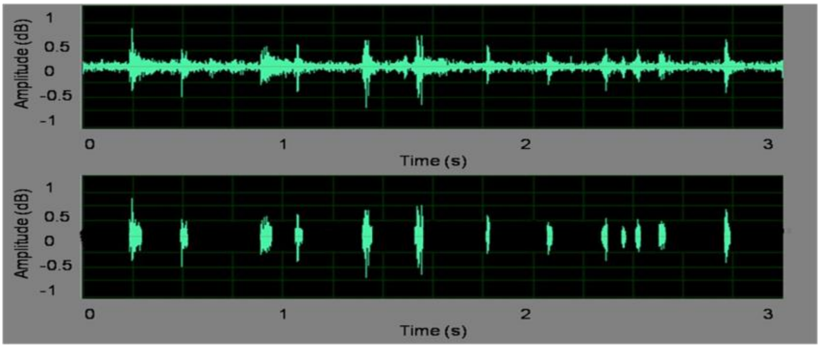

Figure 6.4 Continuous recording of sounds (top) and individual pecking sounds (bottom) as extracted by the algorithm.

6.2.6 Sound classification

The sum of the power spectral density vector was calculated for a frequency range between 1 and 5 kHz in order to identify whether the sound is a peck or not. The frequency range was identified because the peck and the other sound signals have very different frequency content. Based on this, the threshold value can be chosen in the ranges that differentiate the other sound from the pecking sound signal. In this research, an adaptable threshold was chosen instead of a fixed threshold because the frequency contents of pecking and other sound signals are not stable and not easily distinguishable. Every individual sound signal was automatically calculated by the algorithm to give a new and correct threshold value. Each threshold was defined as 0.8 per cent of the maximum signal. However, it should be noted that the noise level and acoustics at a commercial broiler farm are different from the laboratory environment, which can affect the resulting signal. Therefore this should be taken into account when choosing the threshold.

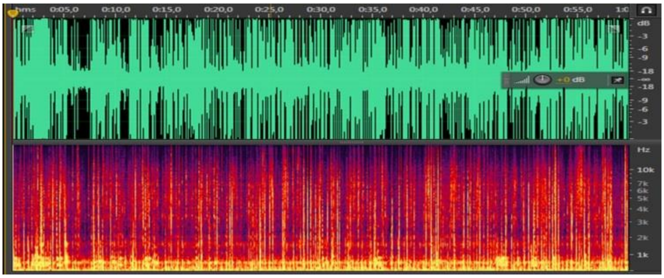

Figure 6.5: Spectrogram of a continuous sound represented in the time domain (top) and in the frequency domain (bottom).

After threshold definition, the algorithm classifies the sound based on a sudden increase of amplitude in both spectrogram(s) and wave forms together with a subsequent decrease. Figure 6.5 shows a spectrogram of a continuous sound consisting of several individual pecks. If the sum of the density is below the threshold in the frequency band, the signal is characterised as a peck.

6.2.7 Feed intake calculation

The feed intake of chickens was automatically measured by a pecking sound detection algorithm and continuously recorded by a weighing system during the experiments. The feed intake is the quantity (g) of feed ingested by chickens with each peck. The feed intake per peck (FIPP) used was 0.025 g (Aydin, Bahr, et al. 2014). Based on this information, calculation of the average feed intake per experiment (FIPE) is defined as: FIPE=FIPPxNPPE. This equation multiplies the feed intake per peck (FIPP) by the total number of pecks per experiment (NPPE). Finally, the feed intake results from the proposed algorithm were compared with the weighing scale data as a gold standard.

6.3 Results and discussion

The main goal of this study was to improve the existing algorithm to enable accurate measurement of the feed intake of broiler chickens while the birds were all pecking at the same time. All sounds were processed and classified as either "pecking" or "other sound" using the proposed algorithm. Table 6.1 shows the total number of pecking sounds identified automatically by the algorithm. The results presented are based on sounds recorded in laboratory conditions using a total of 10 birds.

The second main goal of this research was to develop a continuous monitoring system for further research and commercial use which can measure the absolute amount of feed intake of broiler chickens at group level in farm conditions. In order to achieve this aim, all sound data were analysed by the algorithm to detect the total number of pecks in each experiment. Additionally, feed intake was recorded by a weighing system and the data were linked to the results from the sound algorithm (see Table 6.1).

The algorithm results were compared to reference feed intake values obtained through weighing system measurements. The relationship between feed intake obtained using the algorithm and feed intake recorded by a weighing scale was investigated and a linear relationship between these two variables was identified. A linear regression test was performed to define the coefficient of determination and resulted in $R^2 = 0.994$. In addition to the high correlation, 86 percent of feed intake was correctly monitored using sound analysis. However, it will be necessary to overcome a number of technical challenges in order to develop the proposed algorithm so that it will work under field conditions.

The most important of these challenges is that each feeder in farm might be easily modified by adding a very cheap microphone to rapidly and correctly measure the feed intake of chickens. The real-time nature of the proposed algorithm makes it attractive as a means of measuring the absolute amount of feed intake by chickens in commercial broiler farms. It will be particularly useful in broiler houses where reliable measurement of feed intake is important in order to achieve the right feed conversation rate, calculate the feed wastage, define the eating period, monitor dynamic feeding behaviour and assess the health and welfare of broiler chickens.

Some methods of measuring the feed intake of chickens have previously been presented in the literature. For example, two algorithms for determining individual bird feeding statistics and stereotyped pecking behaviour from time-series recordings of feed weight were developed by Gates and Xin (2008). Their research evaluated the effects of algorithm tuning parameters, including thresholds for changes in weight and sequential number of stabilised readings, arithmetic moving average for meal tare values, and the sampling frequency of feed weight recordings.

They conclude that the lower sampling frequencies are acceptable for determining hourly (or greater) feed consumption. The results presented here are not directly comparable to those of Gates and Xin (2008) since their application refers to feed weight recordings, which is different from our non-invasive sound-based methodology.

Table 6.1: Accuracy results for the proposed algorithm.

Experiments	Time (min)	NPPE (Algorithm)	FIPE Algorithm (g)	FIPE Weighing Scale (g)	Accuracy (%)
1	60	3952	99	111	89
2	60	6018	150	177	85
3	60	5986	150	174	86
4	60	4211	105	121	87
5	60	4231	106	123	86
6	60	7636	191	230	83
7	60	6182	155	184	84
8	60	8692	217	265	82
9	60	3480	87	104	84
10	60	5994	150	185	81
11	60	6199	155	189	82
12	60	2948	74	81	91
13	60	5984	150	176	85
14	60	1414	35	38	93
15	60	1582	40	43	92
16	60	3715	93	108	86
17	60	6160	154	173	89
18	60	4360	109	124	88
19	60	4200	105	117	90
20	60	4160	104	122	85
21	60	3680	92	105	88
22	60	5880	147	172	85
23	60	4000	100	126	79
24	60	3880	97	111	87
Total/Avg.	60	114544	2865	3359	**86**

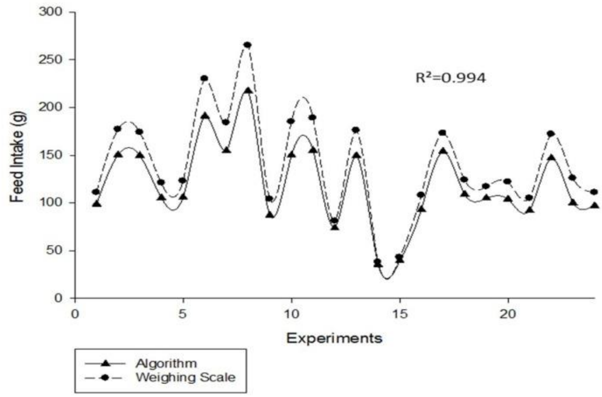

Figure 6.6: Correlation between feed intake measured by algorithm and feed intake recorded by a weighing scale.

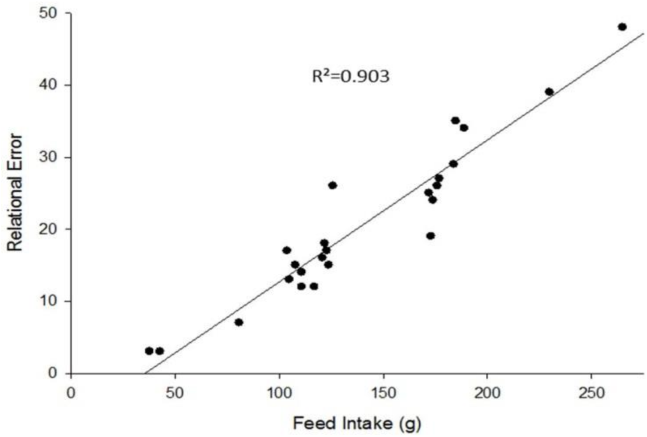

Figure 6.7: Correlation between feed intake and relational error of algorithm.

Although the accuracy of the proposed system remained at 86 percent, as can be seen in Table 6.1, there was a strong correlation (R^2=0.994) between the results from the algorithm and the data from the weighing scale (gold standard). Furthermore, the correlation between feed intake and the relational error of the proposed system was investigated. A strong linear correlation was found between these two variables, giving a coefficient of determination of R^2=0.903. As can be seen in Figure 6.7, when the feed intake was high (265 g), the relational error of this system was also higher (47 g). This means that the accuracy of the proposed system was lower when the feed intake was high. The proposed system could not detect the pecking sounds made by broiler chickens with higher accuracy when all the birds were eating together because some pecking events by different chickens occurred at exactly the same time with the same amplitude and frequency levels. However, the accuracy of the system can easily be improved in future research by making use of this linear relationship between feed intake and the relational error. In any case, the applicability of the approach should be tested under farm conditions for a more accurate evaluation. It should also be stressed that although the algorithm was tested on 10 broiler chickens under laboratory conditions, the results showed that the algorithm will be extremely useful for studying the feeding behaviour of chickens in an objective way in future research.

6.4 Conclusions

This paper proposed an improved algorithm to detect the pecking sounds made by broiler chickens at group level while the birds were all eating together. Furthermore, the results of the algorithm were compared with reference feed intake values obtained through weighing system measurements and video observations. The relationship between feed intake obtained with the algorithm and feed intake recorded by a weighing scale was investigated and the results revealed that there was a very strong correlation between these two variables (R^2 = 0.994). In addition to the close correlation, 86 percent of feed intake was correctly monitored using sound analysis. However, applying the method under field conditions will probably introduce problems which may affect the accuracy of the algorithm. For example, sounds from the ventilation or feed dispenser will introduce new sounds besides pecking. This will affect the frequency content that is evaluated by the algorithm. However, these problems can be solved by studying and estimating the expected noise sequence and fine-tuning the algorithm. Furthermore, animal age and various pathological conditions are believed to affect the frequency content of pecking signals and require further investigation. However, it is clear that sound monitoring could be used to define the feed intake of broilers. The results suggest that this continuous monitoring system has the potential to be used as a tool to monitor the feeding behaviour of broiler chickens. The advantage of this system is that measurements can be made continuously throughout the life-span of a flock, in a fully automated, completely non-invasive and non-intrusive way. The results also suggest that it will be possible to test the system in field conditions, due to its low cost and the applicability of the technique in the field. Apart from sound-based monitoring of broiler chickens housed in groups for breeding purposes, the real-time dynamic feed intake data provide an important basis for research into broiler feeding behaviour and welfare. Thus, future research should focus on sound-based technology to assess the health and welfare of broilers by accurately and continuously measuring feeding behaviours using sound monitoring under different commercial farm conditions.

Chapter 7

General discussion and conclusions

7.1 Problems of modern livestock and disadvantages of manual assessment

Modern livestock production systems face serious problems. Due to an increase in the worldwide demand for animal products, the situation is becoming even worse. It is very difficult to guarantee animal health, animal welfare, reduced environmental impact and productivity. As a result of the upward trend in worldwide demand for animal products, it is clear that animal production will not decline in the next 5-10-50 years. In this work, we have focused on one main problem: how to monitor animal welfare in today's modern broiler production systems.

In Europe, research organisations have invested a lot of money and work in developing a method to evaluate and score animal welfare; for example, a systematic approach to animal-oriented assessments was proposed by the European Research Project: Welfare Quality. This project developed many standardised animal-based measures for each welfare criterion. It proposed that experts should be sent to different livestock houses in Europe to assess the measures developed either on-farm or at slaughter. It is expected that this will take place at the end of a fattening period or once a year (Blokhuis and Haar 2010). There is a trend among animal welfare researchers to extend this method to create a procedure that can be applied in the field. In that vision, each European farmer would pay for one day of assessment every year to score the welfare of his animals. We see serious disadvantages in this approach: the main problem lies in the fact that this human evaluation of animal welfare and behaviour takes a long time. For example, the average time needed to apply the entire Welfare Quality protocol to growing pigs on farms is six hours and twenty minutes (Temple et al. 2011), which does not include the time required for travel. It is completely impossible to visit a high percentage of all livestock houses since each visit takes a serious amount of time. Another problem is that manual scoring by experts is only a momentaneous “snapshot” of a continuously changing process. Thus a very limited piece of information is used to score or judge a rather complex process. The results of momentaneous scoring are useless for the animals which are undergoing the process. To be efficient and realistic, fully automated monitoring systems should be used continuously to score and make judgements in real time (Temple et al. 2011).

However, the procedure is very expensive as a consequence of the human intervention which involves a large amount of time and many hours spent travelling, scoring, analysing and reporting. The claimed cost of 500 euros per visit is not realistic. An invoice of 1500 euros per assessment is more realistic but is a lot of money for the added value provided to the farmer. Our proposal is to analyse whether fully automated technology can monitor welfare problems in broilers on a continuous basis. Automation of animal measures using modern technology such as image and sound processing or sensors and sensing systems and real-time modelling enables continuous assessment of livestock health, welfare and performance. This will improve the effectiveness and efficiency of existing welfare assessment protocols by providing early warning signals so that action can be taken in good time in order to prevent welfare problems.

In this PhD research, images and sounds were used as measures for the status of broiler chickens in order to monitor various behaviours in different environments. When all the results of the previous chapters are taken into account, we may conclude that the features of the image and the dynamics of the sound signal revealed the biological status of broiler chickens. This thesis has explored the potential for using vision and sound-based technologies, real time analysis and monitoring techniques on broiler chickens. As mentioned in Chapter 1, an increase in the amount of technology available together with an evolution in acquired knowledge will provide health monitoring systems for animals which could increase their quality of life. The results of this thesis show that monitoring of audiovisual features over time, be it over a long period of time (during the developmental phases of growth) or on a smaller scale (within the pecking time), shows that specific features hold information about the biological status of the animal.

A number of fully automated monitoring applications based on a PLF approach were investigated and it has been proven in this thesis that continuous bird monitoring is beneficial and feasible as a means of enhancing broiler welfare and management. Using data collected from cameras and microphones, simple data-based input-output modelling can identify the changes occurring in the system due to either environmental factors or animal-induced factors. The challenge is to carry out detection and prediction online in the field. Information can be continuously monitored and changes can be detected within seconds using simple calculations which involve small amounts of calculation power. Fast data acquisition and processing technology is crucial. Changes are detected or predicted immediately so that the person in charge or the person who understands the animal physiology can see what is happening. Technology can bring clear benefits in livestock production, including early detection, trend extraction, and processing of huge dynamic data.

The **general hypothesis** of this thesis was to explore whether technology can assist the eyes and ears of a farmer in identifying welfare issues in large groups of broilers. Two objectives based on vision and sound technology were formulated and the use of image and sound analysis algorithms was investigated. These algorithms can be implemented in real time and can be used continuously over a variety of assessments to extract information about the physiological and behavioural status of the broiler chickens monitored.

In Chapter 2, the welfare of broiler chickens in terms of ease of locomotion was investigated. Activity was studied in relation to gait score in order to identify a quantitative measure of lameness in broilers. There are several causes of lameness in broiler chickens (Bradshaw et al., 2002). However, they can be classified into two groups: developmental abnormalities and infectious diseases. One of the most common leg distortions in broilers with developmental abnormalities is varus-valgus deformation of the intertarsal joint (Sherlock et al. 2010), while infectious disorders are thought to cause the most severe cases of lameness (Kestin, Adams, et al. 1994).

Leg disorders have economic and welfare implications. Broilers with serious leg problems cannot walk to the feeders or feed properly, resulting in reduced body weight, and consequently they are culled. Reducing the number of leg disorders would also improve the health and welfare of broilers (Shimand et al. 2012). When severe lameness is observed in an animal, it is usually already too late to recover the situation. Iceberg indicators which are only measured at the end of a fattening period do not show when the problem started. It is important to know when a problem starts as it might then be possible to resolve it. The best way of solving problems is to detect them as soon as possible, and continuous automated monitoring is essential if this is to be effective.

7.2 Automated measuring of health and welfare indicators in modern livestock

The use of sensors and sensing systems in the house and on-line measurement may provide the farmer with continuous information on the activity status of animals. Sensors and sensing systems are crucial for automatic measurement of animal health and welfare and consequently are very important to the development of integrated monitoring systems for livestock production. From the hygiene viewpoint, image and sound systems have the advantage of not requiring any physical contact with the animal and enable a monitoring technique that has no influence on the living organism.

Computers with high computational power and remote sensing systems have great potential in livestock production. Technology overcomes the problem of human subjectivity in decision making and offers continuous data acquisition. In many cases, continuous sampling provides more detailed information than human senses can obtain from limited periods of observation. An integrated monitoring system collects continuous information from the animal non-intrusively. It then processes the data and provides the farmer with recommendations.

The new aspect presented in this thesis is the evidence that Precision Livestock Techniques offer continuous monitoring and welfare prediction in broiler chickens. Several applications were explored in order to assist the eyes and ears of a farmer, or at least reduce the workload associated with manual on-farm assessment, by automating the collection of some measures using modern vision and sound technologies in sensors and sensing systems.

According to Hester, the relationship between lameness and reduced activity is not clear from the literature (Hester 1994). Chapter 2 investigated the relationship between gait score and activity. Chicken locomotion was scored by experts and five birds per gait score were placed in different cages. Images were then captured continuously in order to monitor the group activity of broilers. There was a significant and non-linear relationship between bird activity and lameness of the birds ($p > 0.05$). Bokkers showed that the high body weight of birds may be considered as a physical restriction on activity and presumably on normal behaviour (Bokkers et al. 2007). However, we found that the most active chickens were the GS3 group, which had the highest body area (307.42+/-19.19b cm^2) during the experiments. The relationship between body weight and gait score was also significant ($p < 0.0001$) and non-linear. The results showed that, in this specific context, the activity information for a group of birds over the entire environment (five birds with the same gait score per cage) is sufficient serve as a lameness indicator which can identify birds with a high gait score (GS4 and GS5.

However, just monitoring the activity of a group of birds over the entire environment (five birds with the same gait score per cage) was not an ideal way of assessing broiler welfare because chickens could exhibit different activity responses due to the interactions between birds when they were housed together, as they would be in commercial farm conditions. Having discussed the monitoring of separated bird groups in Chapter 2, Chapter 3 of the thesis goes on to describe a study in which all fences between the pens were removed and all gait score groups were merged into a single pen for individual monitoring.

Following the study conducted in a strictly controlled cage process, broiler lameness was then assessed in a more complex situation (all birds merged in a single pen). Here, activity information was used to extract information about the lameness of birds, and exploration behaviours were introduced as an indicator for lameness in broiler chickens. Chapter 3 therefore enabled us to evaluate our next hypothesis, which stated that an automatic image monitoring system can be used to determine activity and exploration behaviours of broiler chickens and link them to their lameness degree (gait scores). After looking at the activity level of broiler chickens, exploration behaviours were examined. Here, information about the status of the birds as a group was not obtained on the basis of the number of pixels covered by birds in the image; instead a colour tracking method was developed. This was based on the idea that activity and exploration behaviours change according to the physiological status of the birds, in this particular case the lameness status. This was illustrated using activity and exploration behaviours in broiler chickens.

Based on the results, it is concluded that activity is highly correlated with use of space by the birds. It was found that GS0 and GS3 chickens explored almost the entire compartment. However, GS3 chickens always explored most space, represented by the percentage of pixels. Some studies show that birds are motivated to walk long distances for feed, which may also explain the use of space by GS3 chickens in particular (Noble et al. 1996; Bokkers et al. 2007). Chickens exhibit very distinct foraging behaviour, which usually accounts for between 50 and 90 percent of their time budget under free ranging conditions. Foraging behaviour is strongly linked to locomotion and, therefore, active chickens are assumed to use more space (Haas et al. 2010).

With regard to activity, it is concluded, that merging the different gait score groups into one flock may alter certain behaviours, such as social or foraging behaviour, but does not have an impact on the measurable activity levels. In the case of exploration behaviour, a certain gait score seems to be strongly related to activity level, and therefore the exploration behavioursmay also be a measure for lameness itself. To monitor the biological status of birds it is important to track individual changes in the features investigated. In contrast to the group level monitoring described in the previous chapters, Chapter 4 describes studies in which animals were individually monitored using a top view camera.

Therefore in Chapter 4, a different camera system which has zoom function was used to capture locomotion behaviours and body posture parameters of individual broiler chickens in order to classify specific behaviours such as standing or lying. The objective was to measure the frequency of lying and standing as a sign of gait score level due to lameness.

The X-position, Y-position, orientation and back area of individual chickens in the continuously recorded images were quantified in order to assess whether the features studied (number of lying events and duration of the latency to lie down) were related to lameness. This method of individually assessing locomotion and posture behaviours of broilers could lead to a better understanding of the relationship with lameness. The absolute values for the body features as such were not studied; the focus was on the interrelationship between them, for example, between the x-y coordinates of the animal centre in the pen as a function of time and the top view area of the chicken. This approach was much more detailed than the analysis of chicken activity and exploration behaviours. Furthermore, the importance of individuality and intra-subject variability was stressed. The first hypothesis was proven based on the results of Chapter 4 as there was a clear correlation between these variables (activity, exploration behaviour, body posture parameters) and lameness. The results of this study also showed a clear correlation (R^2 = 0.893) between gait scores and lying behaviour in broiler chickens and were similar to the results obtained by Weeks et al. (2000). As concluded in the study by Weeks et al. (2000), sound broilers averaged 76 percent of 23 hours lying and this increased significantly to 86 percent of 23 hours in lame birds. The automatically extracted latency to lie down (LTL) was evaluated and the results showed a similarity with the results of Weeks et al. (2002) and Berg and Sanotra (2003).

As also concluded by Rushen et al. (2012), in order to identify the effects of gait score on broiler behaviour more accurately, this automatically obtained lying information can be combined with other automatic behaviour analysis systems, such as measuring the activity levels of chickens in order to detect the degree of lameness (Aydin,et al. 2010) and/or detecting the optical flow patterns in broiler chicken flocks as suggested by Dawkins (2009 and 2012).

In addition to previous findings in cows and pigs, PLF technology proved to be effective at detecting lameness in broilers. Other studies have proved its effectiveness in detecting lameness in large animals. However, the idea of using this technology for broiler chickens has never been accepted as there are thousands of animals in one confined space and side view monitoring is not possible.

However, new technological developments are making it much more feasible to monitor thousands of animals. As technology becomes more widespread and cheaper, new products are being developed and used in studies. For instance; the 3D Kinect camera (Microsoft Corp., Redmond, WA) is a fast and affordable camera which has been increasingly used in the last two years to develop real-time applications for human health, such as rehabilitation systems, respiratory motion monitoring systems (Xia and Alfredo 2012) and stride-to stride gait variability measurement systems to predict falls in elderly people (Stone and Skubic 2011). The depth sensor of the Kinect has a 57 horizontal and 43 vertical angular field of view and a maximum image throughput of 30 frames per second. The camera could provide a depth image size of 640 x 480 pixels with 1 cm resolution at a distance of 2 m from the cow (Andersen et al. 2012). The depth values were obtained using an infrared projector that projected a known light pattern onto the object, and an infrared sensor that detected the reflected light patterns, analysed the distortion and produced the depth image (Andersen et al. 2012). Based on this depth information, it will be possible to monitor lying events in broiler chickens continuously and precisely in future studies and on commercial farms in order to detect lameness in birds.

In previous chapters, broiler responses were continuously monitored and the lameness of birds assessed by measuring different types of variable, such as activity levels, exploration and locomotion behaviours and body posture parameters, using image processing technologies. However, a continuous monitoring tool based on an image processing technique is not sufficient on its own to assess broiler behaviour, health and welfare. This led us to evaluate the next hypothesis, presented in Chapter 5, which stated that automatic recording of pecking sounds from broilers allows measurement of feed uptake and assessment of the feeding behaviours of chickens in real time. Therefore, having investigated lameness in broiler chickens using different monitoring techniques based on vision technology, feeding behaviour was examined using sound analysis. Here, sound technology was used instead of vision to obtain information about the pecking and feeding behaviours of broilers. This method (sound analysis) has been used several times in different ways to identify chewing and biting in cows, and to measure feed intake by cattle (Laca and Vries 2000; Clapham et al. 2005). In these studies, a microphone was attached to each animal for recording. This may be realistic with big animals such as cows and pigs but not for broiler chickens. Thus the pecking sounds of 12 individual, 28-day-old, male broiler chickens were recorded using a microphone that was attached to the feeder instead of studying animals in laboratory conditions.

The results show that 93 percent of the pecking sounds were correctly identified by the algorithm, whereas 7 percent of the identification results were false positives. In addition to pecking sound identification, the relationship between feed uptake, feed intake and number of pecks was investigated and a linear relationship between these variables was identified. In addition to the high correlation, 90 percent of feed intake was correctly monitored using sound analysis. As the correlation between the number of pecks and feed intake of chickens was very high (R2 = 0.985), the results suggest that this pecking sound detection system has potential to be used as a tool to monitor the feed intake of chickens. The advantage of this system is that measurements can be taken continuously throughout the life-span of a flock, in a fully automated, completely non-invasive and non-intrusive way.

In contrast to pecking sound detection for an individual bird as described in Chapter 5, Chapter 6 moves from an easy process to a slightly more complex situation to detect pecking sounds for a group of chickens while multiple birds were eating at the same time.

Ten male, 39-day-old, broiler chickens were housed around a feeder in the cage and all sounds were recorded by a microphone that was attached to the feeder. The existing algorithm was improved and used to detect the pecking sounds from 10 broiler chickens while the birds were all eating together. The feed intake of the broiler chickens was obtained by analysing the pecking sounds. The results of the algorithm were compared to reference feed intake values obtained through weighing system measurements. The relationship between feed intake obtained with the algorithm and feed intake recorded by a weighing scale was investigated and a strong relationship between these two variables was identified. In addition to the high correlation, 86 percent of feed intake was correctly monitored using sound analysis. Since the correlation between the feed intake obtained with the algorithm and feed intake recorded by a weighing scale resulted in a very high R^2 = 0.997, the results suggest that this continuous pecking sound detection system has the potential to be used as a tool to measure the feed intake and feeding behaviour of a group of chickens around a feeding pen. The results also suggest that it is possible to test this system in field conditions, thanks to the low cost and applicability of this technique. Thus, future research should focus on sound-based technology to assess the health and welfare of broilers by accurately and continuously monitoring feeding behaviours.

The fully-automated, non-invasive monitoring systems developed can be used to assist the eyes and ears of farmers and stockmen where monitoring is concerned, but also provide the farmer with relevant real-time management information. Early warning systems such as a lameness detector can help farmers and veterinarians to take early action in order to maintain the health and welfare of broiler chickens. Moreover, pecking sound detection systems can be installed on feeders in commercial farms and feed dispensers can be controlled based on the information obtained from a sound-based system. PLF technology can help to implement a realistic animal welfare management system. Livestock management is important for the food security of millions of people today and will be important for the food security of millions more in the coming decades. The use of new technologies, combined with a PLF approach, can improve livestock production while ensuring the health and safety of consumers. The early lameness detection systems which are presented in the vision sections of this thesis (Chapters 2, 3 and 4) can reduce the environmental impact of livestock by reducing morbidity and mortality in broiler chickens. However, a real-time feed intake monitoring system based on sound technology can reduce the environmental impact by controlling additional factors:

1. The quantities of nutrients directly entering the waste stream can be reduced by controlling feed wastage.
2. Increase growth rate and feed efficiency.
3. Minimise losses within the system.

We can therefore conclude that fully automated image and sound analysis can be used in a variety of real-time applications for broilers which are based on developments in vision and sound technology. The audiovisual monitoring methods and the algorithms involved will be highly dependent on the complexity of the organisms monitored and their environment. The key to monitoring the biological status of an individual is to monitor the variation in the calculated parameters over time, whether this is on a small time scale (several seconds) or a large time scale (several days).

Since all animals are CITD (complex, individual, time-varying and dynamic) systems, we need to use appropriate monitoring and modelling techniques to model their responses to certain environmental inputs. The animal will respond in an individual way which means that we need an individual model for each animal. The growth response will be time-varying as it will vary with, for example, the animal's age and health status. The model must therefore be adapted over time. Monitoring and mathematical modelling techniques are proven to be very useful in detecting the health and welfare of broiler chickens. In the field of Precision Livestock Farming, this thesis introduces innovative methods to measure locomotion, posture and feeding behaviours of broiler chickens using image and sound analysis. Although the vision section of this thesis (Chapters 2, 3 and 4) does not develop any novel techniques, it provides a detailed description of several applications of monitoring and modelling techniques relating to broilers, with their advantages and disadvantages. However, the section of the thesis dealing with sound (Chapters 5 and 6) describes a novel technique which was developed and patented (see Patents section at the end of this thesis). The availability of relatively cheap sensors for sound acquisition means that sound technology can be a valuable tool for monitoring the feed intake of broilers. This is the first time that the dynamics of sound signals have been quantified in relation to pecking sounds from broiler chickens for continuous, non-invasive measurement of feed intake.

The most remarkable finding and conclusion of this PhD thesis is that large groups of broilers can be monitored using PLF technology (e.g. non-invasive audiovisual monitoring techniques). By using image and sound analysis for broiler monitoring, we have demonstrated that concepts which have previously been applied to cows can also be applied to individual broilers. Furthermore, the future behaviour of birds can be predicted using mathematical modelling techniques and can be controlled using modern control theory applications.

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Curriculum Vitae

Arda AYDIN was born on November 16th, 1980 in Kesan, Turkey. He followed his primary school at Bigadic, Balikesir - Turkey, and his secondary school at Kesan, Edirne-Turkey. In 1998 he started a degree in Agriculture-Engineering at Trakya University-Turkey, which he graduated in 2002. He received his Master’s degree in Agricultural Mechanization from Canakkale Onsekiz Mart University, Turkey, in 2005. Arda worked as a Research Assistant during three years between 2005 and 2008 at the Faculty of Agricultural Engineering, in Canakkale, Turkey. In September 2008 he was admitted to the Arenberg Doctoral School of KU Leuven, Belgium. During his Ph.D. Arda is first author of 6 peer reviewed journal publications and co-inventor in 1 patent application.

Publications

International Journal Publications:

1. Aydin, A., Cangar, O., Eren Ozcan, S., Bahr, C., Berckmans. D. (2010). Application of a fully automatic analysis tool to assess the activity of broiler chickens with different gait scores. Computers and Electronics in Agriculture. 73: (194-199).

2. Aydin, A., Bahr, C., Pluk, A., Leroy, T., Berckmans, D. (2013). Advanced approach to automatically identify activity and exploration behaviour of birds with different gait score. ASABE. 56(3): (1123-1132).

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2. Aydin, A., Silva, M., Ferrari, S., Exadaktylos, V., Guarino, M., Berckmans, B. (2010). Sound Analysis for Health Monitoring in Commercial Piggeries. Second European Symposium on Porcine Health Management "Pig Health, Performance and Welfare" May 26-28, 2010. Hannover, GERMANY.
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5. Aydin, A., Berckmans,D., Pluk, A., and Bahr, C. (2013). Fully Automated Monitoring Tool to Assess of Activity and Spatial Distribution of Broilers.18th National Symposium on Applied Biological Sciences (NSABS). Gent Belgium
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7. Aydin, A., Bahr, C., Berckmans,D. (2013). A relational Study of Gait Score with Resting Behaviours of Broiler Chickens. Joint European Conference on Precision Livestock Farming (ECPLF) September 10-12, 2013. Leuven, Belgium.
8. Aydin, A., Bahr, C., Berckmans,D. (2013). Measuring Feed Intake of Broilers by Real Time Sound Analysis. International Symposium on Animal Environment and Welfare. Oct 19-22, 2013, China.

Patent

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